Self-Employment and Working from Home Trends in Maryland, 2017-2022

Submitted to
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Summary of Findings

Relying on the monthly individual level Current Population Survey (CPS) Data of civilians aged 25 or above and multiple multilevel generalized estimating equation (GEE) population-averaged models, the findings of this study include:

- Two years after the pandemic started, Maryland has a slower employment recovery than the national average and Maryland industry and occupation mixes have changed from 2017 to 2020. Only few sectors grew. Maryland's typical top two industry sectors*, Health Care & Social Assistance (NAICS: 62*[1]*)* and *Professional Services (NAICS: 54)*, are both shrinking, while *Public Administration (NAICS: 92)* and *Education (NAICS: 61)* emerged to the top in March 2022.
- Maryland has a similar *self-employment* (versus *wage-and-salary employment*) trend with the national average, but a higher *incorporated* (versus *unincorporated*) self-employment rate, particularly after the COVID-19 pandemic started.
- Based on our empirical analysis, among Maryland workers, male, older, or better educated workers are more likely to be *self-employed* instead of in *wage-and-salary* employment. Workers in *Arts, Design, Entertainment, Sports, and Media (SOC:27*[2]*)* and *Personal Care & Service (SOC:39)* occupations have a higher probability of being *self-employed* (versus in *wage-and-salary* employment) than *Management (SOC: 11)* occupations, while most other occupation sectors have lower odds. Industry sector *Agriculture (NAICS: 11)* typically has a higher self-employment rate than other industry sectors.

[1] This is the first two-digit of NAICS 2017 code for industry sectors.

Workers in most sectors that experienced employment growth in Maryland in 2017-2022 are among sectors with the lowest odds of being *self-employed* (versus in *wage-and-salary* employment).

- Among Maryland self- employed individuals, male, younger, less educated, African American (versus White American) self-employed workers are more likely to be *new* (versus *incumbent*), or *full-time* (versus *part-time*) self-employed; being employed in the prior month is more likely to be associated with *incumbent* (versus *new*) self-employment in the current month.
- Our empirical analysis shows that male, better educated, with more employment experience in the prior month, married with spouse's presence, *Management (SOC: 11*) (versus several other sector) *occupations* are more likely to be in *incorporated* (versus *unincorporated*) self-employment. Among Maryland self-employers and compared to *Management* (*SOC: 11*) occupations, the odds of being *new* (versus *incumbent*) self-employed in *Healthcare Support (SOC: 31)* occupations are 7.55 times as high, *Construction & Extraction (SOC: 47)* and *Transportation and Material Moving (SOC: 53)* occupations are also more likely to be *new* (versus *incumbent*) self-employers, *Office & Administrative Support* occupations *(SOC: 43)* are more likely to be *new* (versus *incumbent*) self-employers and *part-time* (versus *full-time)* self-employers, *Installation, Maintenance, and Repair occupations (SOC: 49)* are more likely to be *full-time* (versus *part-time*) self-employers. As *incorporated* and *new* self-employment often create jobs, the relatively high odds of *incorporated* (versus *unincorporated*) self-employment in *Management (SOC: 11)* occupations and the very high odds of *new* (versus *incumbent*) self-employment in *Healthcare Support (SOC: 31)* occupations help those two sectors to be in the short list of growing sectors from 2017 to 2022.
- Compared to the national average, Maryland workers have a clearly higher working from home (WFH) rate, particularly in *Management* occupations *(SOC: 11)* and in the industry sectors of *Real Estate (NAICS: 53), Other Services (NAICS: 81), and Public Administration (NAICS: 92).* After the pandemic lockdown ended, WFH rates dropped both for the United States and Maryland. Those sectors, except for *Other Services (NAICS: 81),* are among the list of Maryland sectors that grew from 2017 to 2022.
- Among Maryland workers, our empirical model shows that female and better educated workers with higher family income are more likely to work from home. Compared to *Management (SOC: 11)* occupations, *Business & Financial Operations (SOC: 13)* and *Computer & Mathematical* Occupations (15) are even more likely to work from home, while most other occupation sectors have lower WFH odds. Compared to *Agriculture (NAICS: 11)*, industry sectors *Utilities (NAICS: 22),* M*anufacturing (NAICS: 31-33)*, *Information (NAICS: 51)*, *Finance & Insurance (NAICS: 52), Real Estate (NAICS: 53)*, *Professional Services (NAICS: 54)*, *Administrative Services (NAICS: 56), Education (NAICS: 61)*, *Healthcare (NAICS: 62)*, *Other Services (NAICS: 81)*, and *Public Administration (NAICS: 92)* have higher WFH odds. Compared to observations with unspecified county locations, *Harford County* has lower WFH odds, while *Montgomery, Prince George's,* and *Baltimore City* have higher WFH odds.
- Maryland workers have higher earnings than average U.S. workers and WFH workers overall have higher earnings than non-WFH workers. In Maryland, WFH jobs are paid averagely $144 more weekly than non-WFH jobs, ceteris paribus.
- Different from the national average, the number of Maryland workers' working hours are rising over time. These longer working hours could partially explain Maryland's slower employment recovery as employers utilize existing workers more intensively, rather than hiring additional workers. Also, it could partially reflect the higher WFH rate in Maryland, as many WFH workers work longer hours.

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Introduction

In recent years, there is an upward trend in alternative work arrangements, such as or self-employment or independent contractors since 1995(Katz and Krueger, 2019) and working from home (WFH) or remote workers more recently in the pandemic. Data from the U.S. Bureau of Labor Statistics (BLS) showed that the self-employment rate is on the rise (Torpey & Robert 2018). As our population is aging, Zhang & Acs (2018) noted that the self-employment rate rises with age in the United States. Maryland has one of the oldest populations in the nation. The rising self-employment could mean a potential paradigm shift for workforce training to increase focuses on non-traditional and entrepreneurial training activities. In the meantime, with the COVID-19 pandemic affecting our current economy and with continuing public health concerns, many workers work remotely or from home. Data from the U.S. Business response survey shows a 13 percent increase of teleworking in all U.S. private sector jobs in the pandemic (Dalton & Groen, 2021). Many American adults who rarely worked remotely prior to the COVID-19 pandemic would like to continue to telework once the pandemic improves (Parker et al., 2020). At this historical junction, this study explores the self-employment and WFH trends in Maryland and investigates how those trends are related to Maryland industry and occupation mixes and how sociodemographic factors affect those trends. Those trend analysis and factor examination can help understand the changing Maryland economy and identify dynamic workforce service or training needs.

Methodology

After explaining the methodology adopted in the study, this study starts with overall snapshots showing that Maryland's industry and occupational mix changed from 2017 to 2022. Then the study first presents Maryland's self-employment trends including different self-employment types, by industry and occupational sectors, and by knowledge-based versus non-knowledge-based sectors. It also touches on earnings profile for self-employment.

[3] The study is completed with research assistance from Kristina Ousley.

With limited observation of self-employed persons' earnings data in Maryland, we are not able to examine self-employment earnings further.

After that, the study describes Maryland's WFH employment trends and contrast that to that of non-WFH employment. It also describes earnings differences between WFH workers and non-WFH workers. Trends by industry and occupation mix are examined as well.

After describing the self-employment and WFH trend data, the study focusses on Maryland alone and empirically examines the contributing factors for self-employment and WFH propensities. Factors driving propensities for different types of self-employment are also examined. The rest of this section explains the data and then model nuances.

Data

The study utilizes longitudinally linked U.S. Current Population Survey (CPS) data compiled by Flood et al. (2015) in the Integrated Public Use Microdata Series, monthly from January 2017 through March 2022. To measure the nuanced entrepreneur types, a nationally well-represented dataset to capture month-to-month employment transitions that covers multiple years with individual-level demographic and socioeconomic details is desired; to capture remote working or working from home with individual worker level details in the pandemic, monthly nationally representative microdata samples is required. The CPS data therefore become the ideal option for this study. As a nationally well-represented reliable employment information of the noninstitutionalized U.S. civilian population, the CPS has one of the highest response rates (90%) among government household surveys (U.S. BLS & U.S. Census Bureau 2006) with extensive longitudinal demographic and socioeconomic information covering many years. The CPS is the best source for self-employment information, as it reports on self-employed individuals not covered in the Current Employment Statistics, includes both unincorporated and incorporated self-employment, and is the source of official statistics on the U.S. self-employment (Zissimopoulos & Karoly 2007).

Households in the CPS are interviewed according to a 4-8-4 rotation pattern: that is, households are interviewed for four consecutive months, dropped out of the sample for the next eight months, and interviewed again in the next four months, after which they leave the sample permanently. The 4-8-4 rotation has the added benefit of allowing the sample to be constantly replenished, with continuity and without an excessive burden on respondents (U.S. BLS & U.S. Census Bureau 2006); however, it only tracks a person for eight sampling months. Although the CPS data contain self-identified information that can cause common method bias (Podsakoff et al. 2003), this is not a major concern in this study. The data cover 63 monthly data points with eight monthly measures for each worker; they therefore avoid the problem of using a single response at a single point in time. In addition, using the well-represented, large-scale, multipurpose national survey data reduces the effects of social desirability bias typically seen in small, single-purpose surveys (Binder & Coad 2013).

Considering most young adults typically do not complete tertiary education and work for a full-time job until age of 25, the data sample for this study is limited to adults aged 25 or up. This is consistent with the U.S. Census measure of education attainment.

Models

This study adopts the multilevel generalized estimating equation (GEE) population-averaged model approach. Due to CPS' special sampling design, each individual only tracks up to 8 months, individual worker level fixed effect modeling for longitudinal studies is not the best model to take the best advantage of the data set. In addition, workers in the same industry or occupation sectors or in the same county could share some common attributes. This clustering data structure calls for more model specification controls than simple individual worker level fixed effects. Basic regression approaches relying on the Ordinary Least Squares (OLS) estimating is limited because the employment outcomes of residents in the same location or neighborhood (i.e., county in this study) or within the same industry and occupation sectors may be correlated, thus violating independence assumptions made by traditional OLS based basic simple regression procedures. This violation is particularly relevant to estimates of the variability of estimates.

Two modeling approaches are commonly used to estimate the associations between locational or industry/occupation sectoral attributes and individual-level employment outcomes in multilevel studies. Mixed-effects models use maximum likelihood estimation. Population-averaged models typically use a GEE approach. Hubbard, et al, (2022) noted while mixed models involve unverifiable assumptions on the data-generating distribution, which lead to potentially misleading estimates and biased inference, the estimation-equation approach of population-averaged models provides a more useful approximation of the truth. In addition, our data has multiple layers of clustered structure—across different months for each individual person, across different workers of each industry sector, across different workers of each occupation sector, and across individual civilians of each county. Those clusters are not necessarily nested or hierarchical and therefore multilevel mixed-effect hierarchical modeling would not be a good fit for our data structure.

To observe the industry and occupation sectoral sensitivities and county level disparities, this study incorporates into the GEE model multiple fixed effects from industry and occupation sectors, as well as counties, in addition to controlling for time effects (year and month), COVID-19 pandemic period, and other variables.

This study presents the GEE population-averaged effects to illustrate the marginal effect of occupation and industry sectors, county, individual age, gender, race, education attainment, income level, and other workers' socioeconomic attributes, controlling for all other factors. Godfrey (2015) reported an upward trend in women becoming self-employed, accompanied by a decline in the wage gap between *self-employed* women and self-employed men. During the pandemic, Mendes & Lewin (2021) found that *self-employed* individuals suffered more financially than *wage-and-salary* workers overall, though with less difficulty than *wage-and-salary* workers in certain business sectors, based on the CPS data of May 2020 through May 2021; women and non-whites were also found affected more adversely than other groups. For WFH trends, there are clear sectoral disparities (Dingel & Neiman 2020; Zhang, et al 2022). Those with higher income occupations were also found far more likely to be working remotely than those with lower income occupations (Gaffney et al., 2021).

To model contributing factors for self-employment and WFH propensities, the dependent variables are binomial variables contrasting two categories. Therefore, the study adopts GEE population-averaged binomial logit models. Equation (1) summarize the model specification:

$$P(Y_{it} = 1 \mid X_{\mathrm{kit}}) = \frac{\exp\left(\alpha_0 + \sum \beta_k X_{\mathrm{kit}} + Occ_{it} + Ind_{it} + County_{it} + Time_i\right)}{1 + \exp\left(\alpha_0 + \sum \beta_k X_{\mathrm{kit}} + Occ_{it} + Ind_{it} + County_{it} + Time_i\right)} \quad (1),$$

where *Y* represents five sets of binary dependent variables: being *self-employed* (with value of 1) or in *wage-and-salary employment* (with value of 0), being *newly self-employed* (with value of 1) or *in incumbent self-employment* (with value of 0), being in *incorporated self-employment* (with value of 1) or *unincorporated self-employment* (with value of 0), being in *full-time self-employment* (with value of 1) or *part-time self-employment* (with value of 0), and being in *WFH* jobs (with value of 1) or *non-WFH* jobs (with value of 0). *X* represents *k* individual level variables (age, gender, race, education attainment, marital status, child in household, family income) across individual *i* and time *t. Occ*, *Ind*, and *County* respectively represent occupation sector, industry sector, and county fixed effects. *Time* captures the year and month, as well as COVID-19 pandemic control effects.

To model the contributing factors for earnings variabilities, we adopted the GEE population-averaged Gaussian model. Equation (2) summarize the model specification, where μ_{it} represents random errors:

$$Earnings_{\mathrm{it}} = \alpha_0 + \sum \beta_k X_{\mathrm{kit}} + Occ_{it} + Ind_{it} + County_{it} + Time_i + \mu_{it} \qquad (2).$$

Both GEE population-averaged binomial logit models and GEE population-averaged Gaussian models use individual civilians (aged 25 or above) as the group or panel variable and thus are modeled by variations across different months for each individual civilian. The rest of the study presents the data and model estimates.

For industry sectors, the study adopts the North American Industry Classification System (NAICS) 2017 code system. For occupation sectors, the study adopts Standard Occupational Classification (SOC) 2010 code system. For location, the study adopts county because geographic units with even finer resolution would result in extremely limited number of observations and large potential errors and bias.

Maryland Industry and Occupation Mix Change: 2017 vs. 2022

The COVID-19 pandemic has significantly affected the Maryland economy. While the number of U.S. workers at work (shown as the blue curve in Figure 1) in March 2022 already recovered to around the pre-pandemic level, this is not the case for Maryland workers. Although Maryland has a slightly steeper retirement trend (shown as the red curve in Figure 1) than the national average since the pandemic started, it might not be the entire story. Industry and occupation mix changes might be another important perspective to the changing Maryland economy over the past five years.

When examining Maryland employment by industry sectors from March 2017 to March 2022 in Figure 2, there are several major changes. Partially affected by the COVID-19 pandemic, most industry sectors are shrinking in 2022 compared to 2017; only in the industry sectors of *Public Administration (NAICS: 92*[4]*), Education (NAICS: 61)*, *Administrative Services (NAICS: 56)*, *Management (NAICS: 55)*, *Real Estate (NAICS; 53), Manufacturing (NAICS: 31-33)*, *Mining (NAICS: 21)*, and to a lesser extent, *Finance & Insurance (NAICS: 52)*, there are clear employment increases. Maryland's typical top two industry sectors*, Health Care & Social Assistance (NAICS: 62)* and *Professional Services (NAICS: 54)*, are both shrinking, particularly the former, while *Public Administration (NAICS: 92)* and *Education (NAICS: 61)* jump to the top two Maryland industry sectors in March 2022.

When examining occupation sectors, in addition to the rise in *Education, Training, and Library occupations (SOC: 25*[5]*)*, Maryland employment in *Management (SOC: 11)* and *Healthcare Support occupations (SOC: 31)* also increased, while employment in *Healthcare Practitioners and Technical occupations (SOC: 29)* are shrinking. This is also presented in Figure 2.

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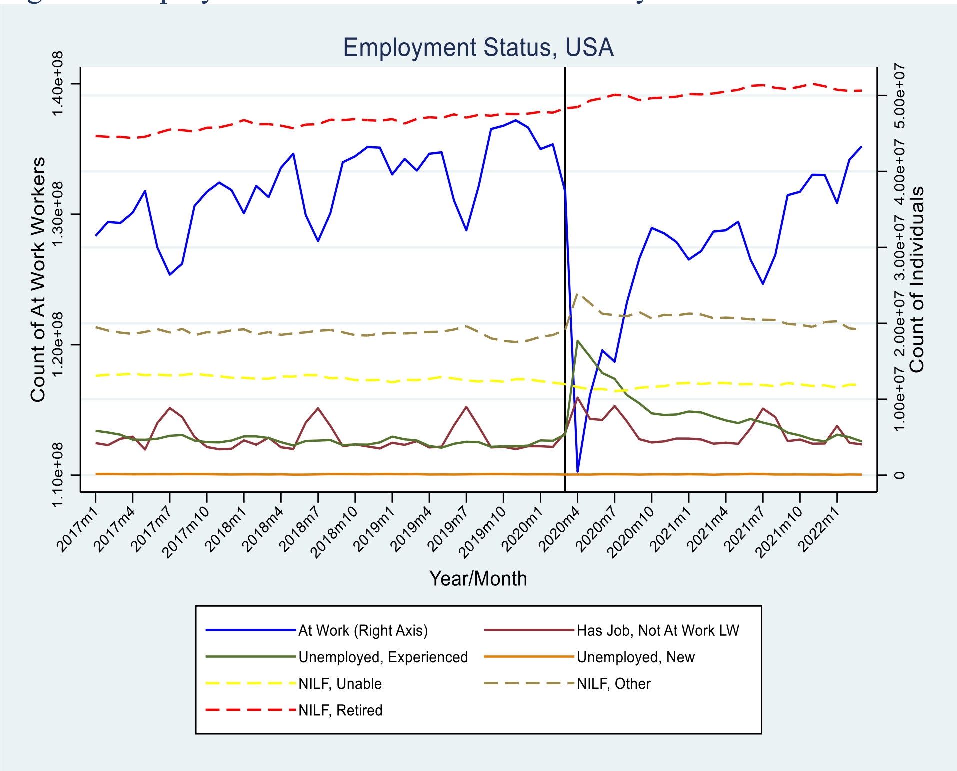
[4] This is the first two-digit NAICS 2017 code for industry sectors.
[5] This is the first two-digit SOC 2010 code for occupation sectors.

Figure 1 Employment Status for USA versus Maryland



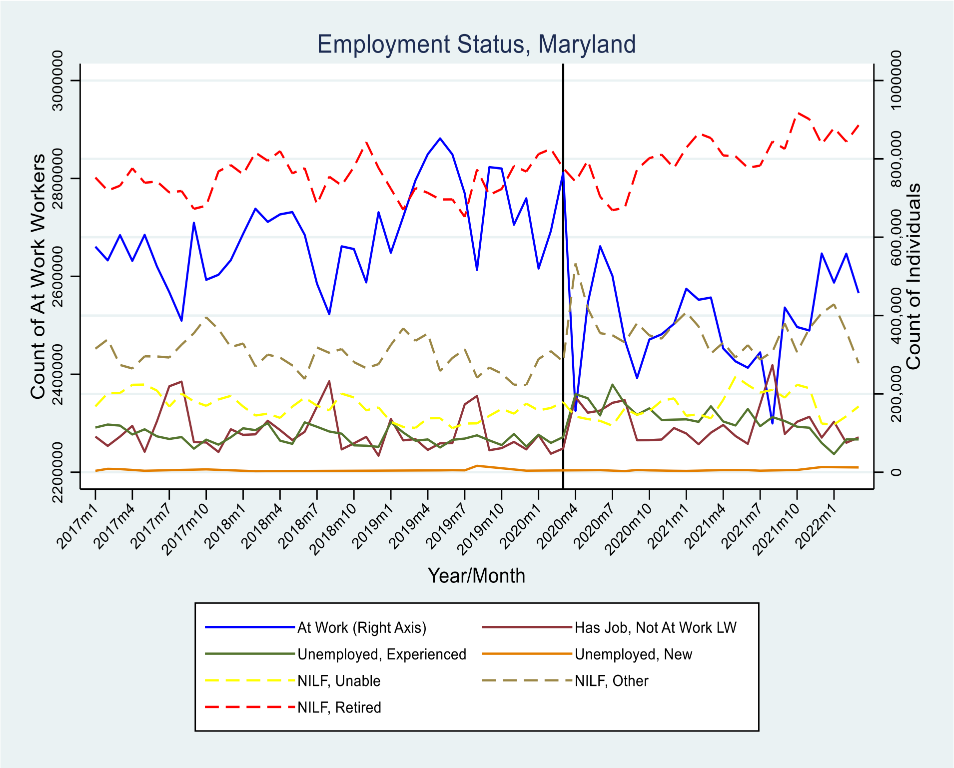
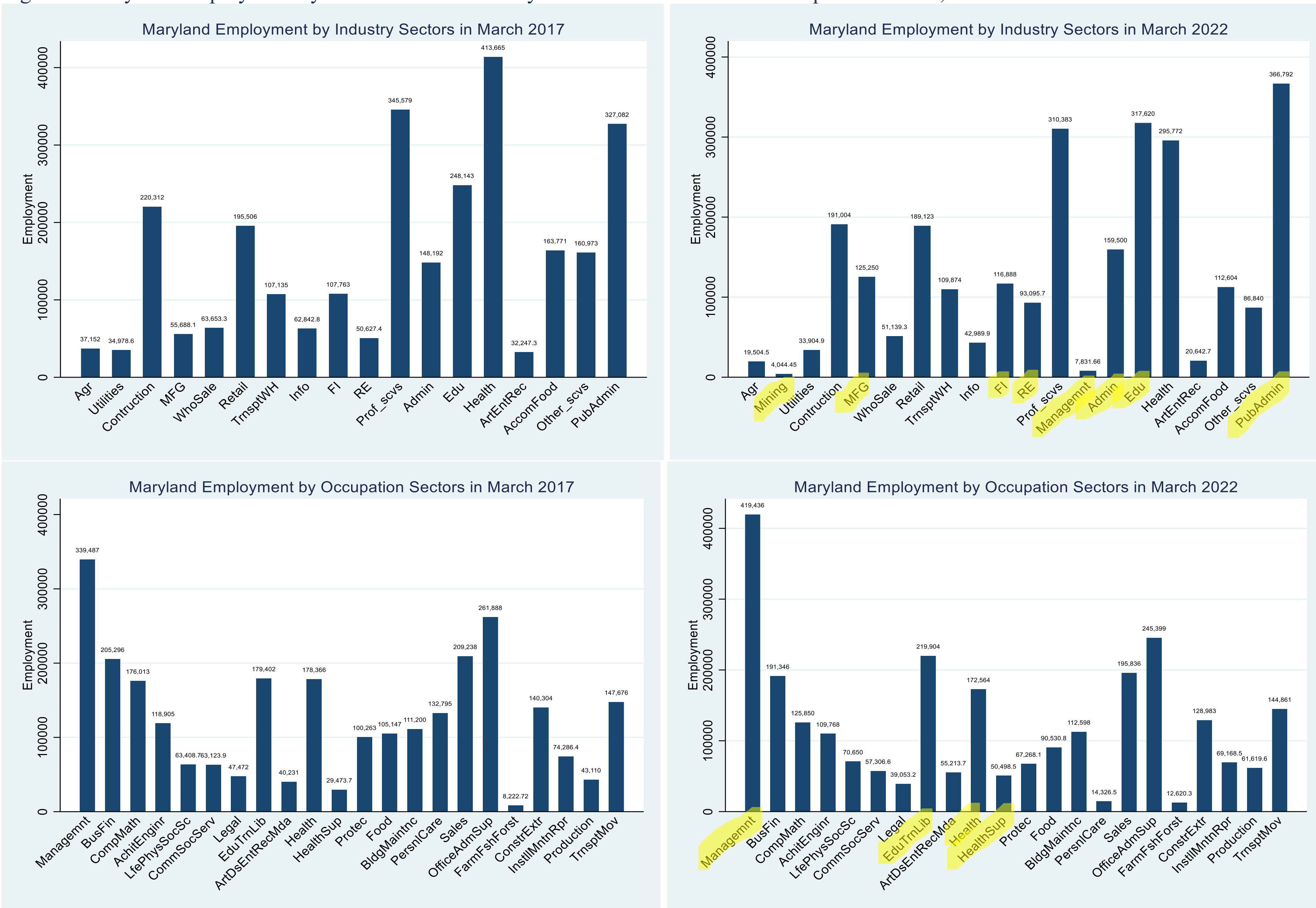


Figure 2. Maryland Employment by NAICS-Coded Industry Sectors and SOC-Coded Occupation Sectors, March 2017 versus March 2022



Maryland's Self-Employment Trends

With the nationally rising self-employment and WFH trend, this section examines Maryland self-employment trends. The changing Maryland industry and occupation mixes in the past five years might be related to Maryland's self-employment and WFH trend.

For the self-employment trend, this study compares *self-employed* workers to *wage-and-salary* employees and drills down into six types[6] of self-employment defined by Zhang (2019): *new* versus *incumbent*, *full-time* versus *part-time*, and *incorporated* versus *unincorporated* self-employment. *New* self-employers are those who become entrepreneurs for the first time, differing from *incumbent* ones. *Full-time* self-employers work more hours than *part-timers*. *Incorporated* and *unincorporated* self-employer have different implications to the economy. The different type nuances reveal different workforce development needs for self-employed workers.

The overall *self-employment* (versus *wage-and-salary employment*) trend over the past five years in Maryland is comparable to the national trend. Across six self-employment types, Maryland has a higher *incorporated* (versus *unincorporated*) self-employment rate, and this is more evident since the start of the COVID-19 pandemic, as illustrated in Figure 3. Since the pandemic started, Maryland also has a slightly steeper increase in *full-time* (versus *part-time*) self-employment, compared to that for the United States overall. With a smaller population and thus a smaller sample in Maryland, it is expected to see more volatility and fluctuations in the six types of self-employment trend, even more so when breaking down by industry and occupation sectors (shown in Appendix Figures A & B).

To make the industry and occupation sector breakdown in self-employment trends more visible, Figure 4 groups the sectors into knowledge- versus non-knowledge-based sectors. Consistent with Zhang (2008), knowledge-based sectors include industry sectors of *Information (NAICS: 51), Finance & Insurance (NAICS: 52), Real Estate (NAICS; 53), Professional Services (NAICS: 54), Management (NAICS: 55), Administrative Services (NAICS: 56), Education (NAICS: 61), Healthcare & Social Assistance (NAICS: 62), Arts, Entertainment & Recreation (NAICS: 71), and Public Administrative (NAICS: 92)*, and occupation sectors of *Management (SOC: 11), Business & Financial Operations (SOC: 13), Computer & Mathematics (SOC: 15), Architecture & Engineering (SOC: 17), Life, Physical & Social Science (SOC: 19), Community & Social Services (SOC: 21), Legal (SOC: 23), Education, Training & Library (SOC: 25), Arts, Design, Entertainment, Sports, & Media (SOC: 27), and Healthcare Practitioners & Technical occupations (SOC: 29).*

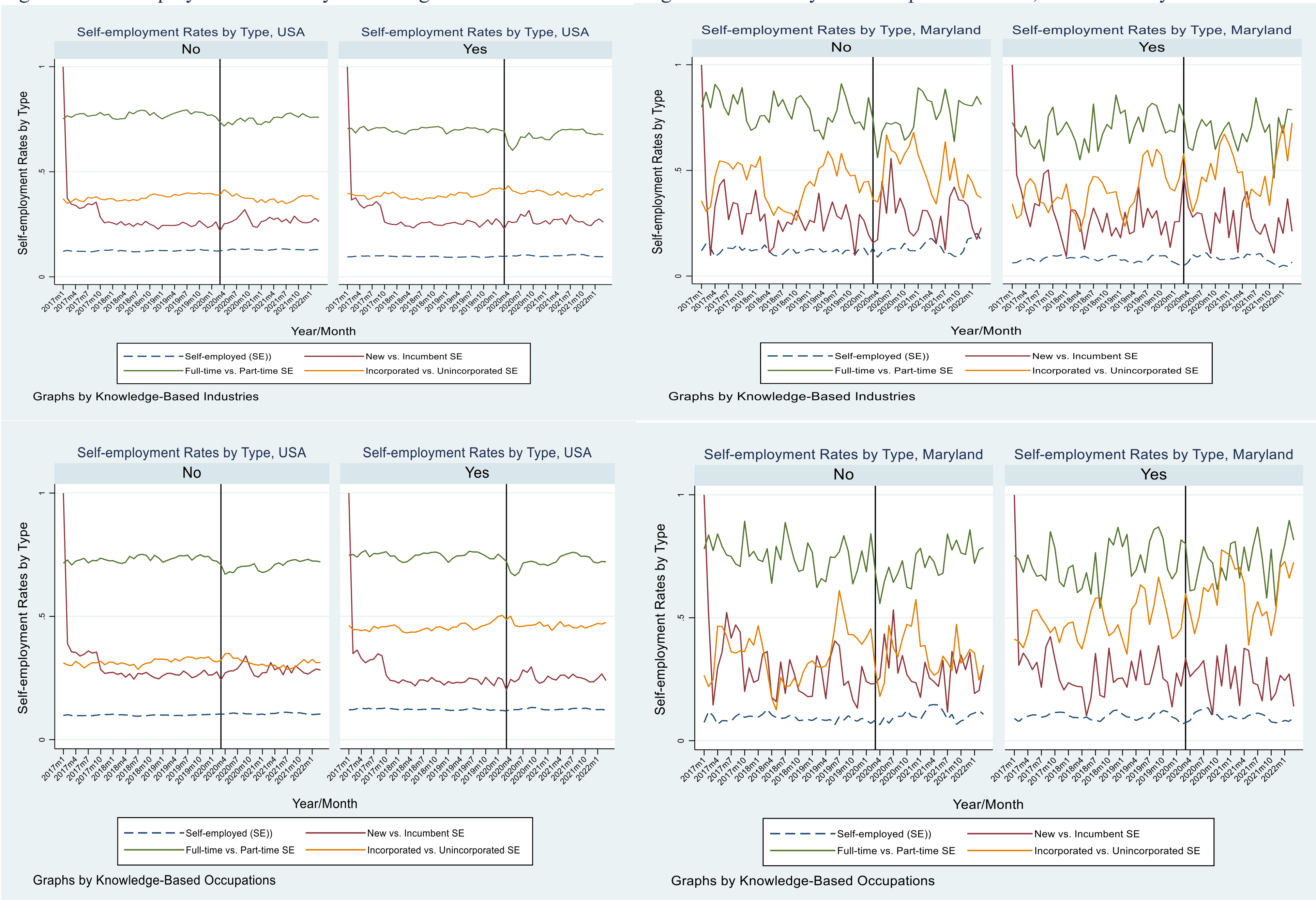
As shown in Figure 4, knowledge-based occupation and industry sectors have higher and rising *incorporated* (versus *unincorporated*) self-employment, compared to non-knowledge-based sectors, for both United States overall and for Maryland[7].

[6] Due to limited samples size, we were not able to sufficient observations to model *opportunity* versus *necessity* self-employment in Maryland for this study. We therefore do not include this pair.

[7] Although knowledge-based industry sectors have lower full-time (versus part-time) self-employment than non-knowledge-based industry sectors, this is not the case for occupation sectors. Broad sector classification does not necessarily always define knowledge sectors accurately.

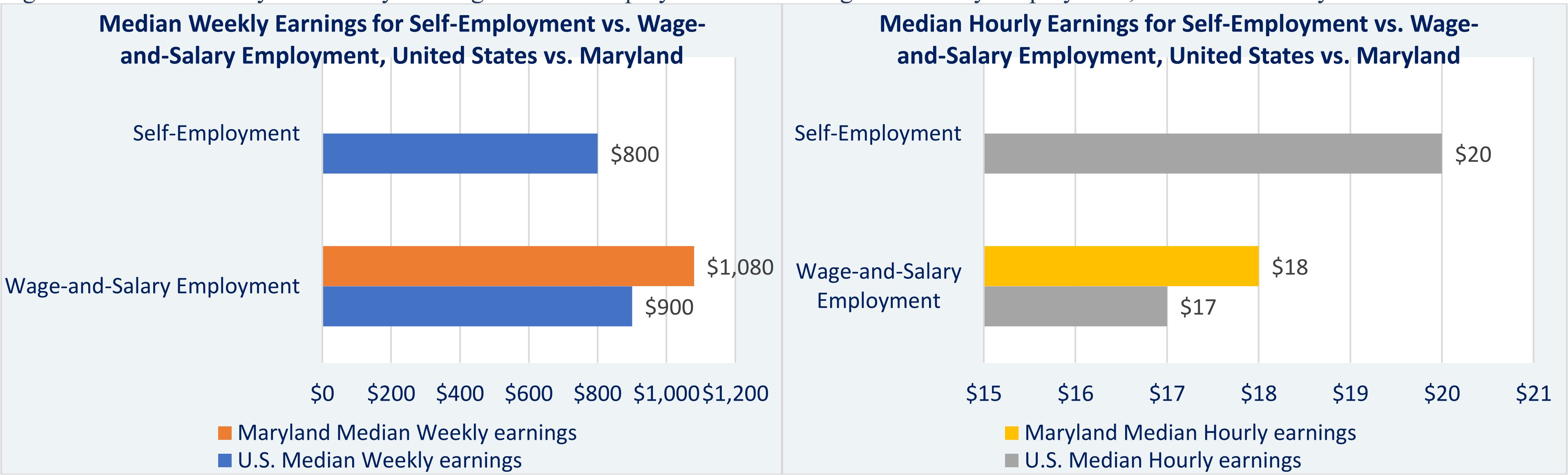
Figure 3. Monthly Self-Employment Rate Trends for USA versus Maryland

Figure 4. Self-Employment Trends by Knowledge-Based vs. Non-Knowledge-Based Industry and Occupation Sectors, USA vs. Maryland



In addition to examining employment trend by its size, the study also examines earnings. As expected, Figure 5 shows that Maryland *wage-and-salary* workers have higher median weekly and hourly earnings than U.S. average *wage-and-salary* workers. In the United States overall, median weekly earnings for *self-employment* are lower than that *for wage-and-salary employment*, though median hourly earnings for *self-employment* are higher across observations in the CPS samples. Hourly earnings are often interpreted as earnings for hourly wages, not necessarily for salaries. This could be part of the reason for this difference. The CPS data does show many more weekly earnings records than hourly earnings records. Across all the observing months (January 2017 through March 2022) for each worker across the United States, CPS data with sampling weights represents 1.89 billion weekly earnings records but only 1 billion hourly earnings records for *wage-and-salary* employment. As a contrast, the weighted sample represents only 5262 weekly or hourly earnings records for *self-employment* across the United States. Many workers, including *self-employed* workers, do not report earnings. For Maryland, the weighted CPS sample represents 38.7 million weekly earnings records and 17.6 million hourly earnings records for *wage-and-salary* employment, but no sufficient representation for self-employment weekly or hourly earnings at all. Therefore, we could not present Maryland's *self-employment* earnings or compare *self-employment* earnings across industry or occupation sectors.

Figure 5. Median Weekly and Hourly Earnings for Self-Employment versus Wage-and-Salary Employment, USA versus Maryland



Notes: The above figure is based on the CPS sample data after applying sampling weights and across all observing months for each worker that represents wage-and-salary employment's 1.89 billion weekly earnings records and 1 billion hourly earnings records, but only 5262 earnings records for self-employment in the periods of 2017-2022 across the whole United States. For Maryland, it represents 38.7 million weekly earing wage-and-salary records and 17.6 million hourly earnings wage-and-salary records, but no sufficient representation for self-employment weekly or hourly earnings at all.)

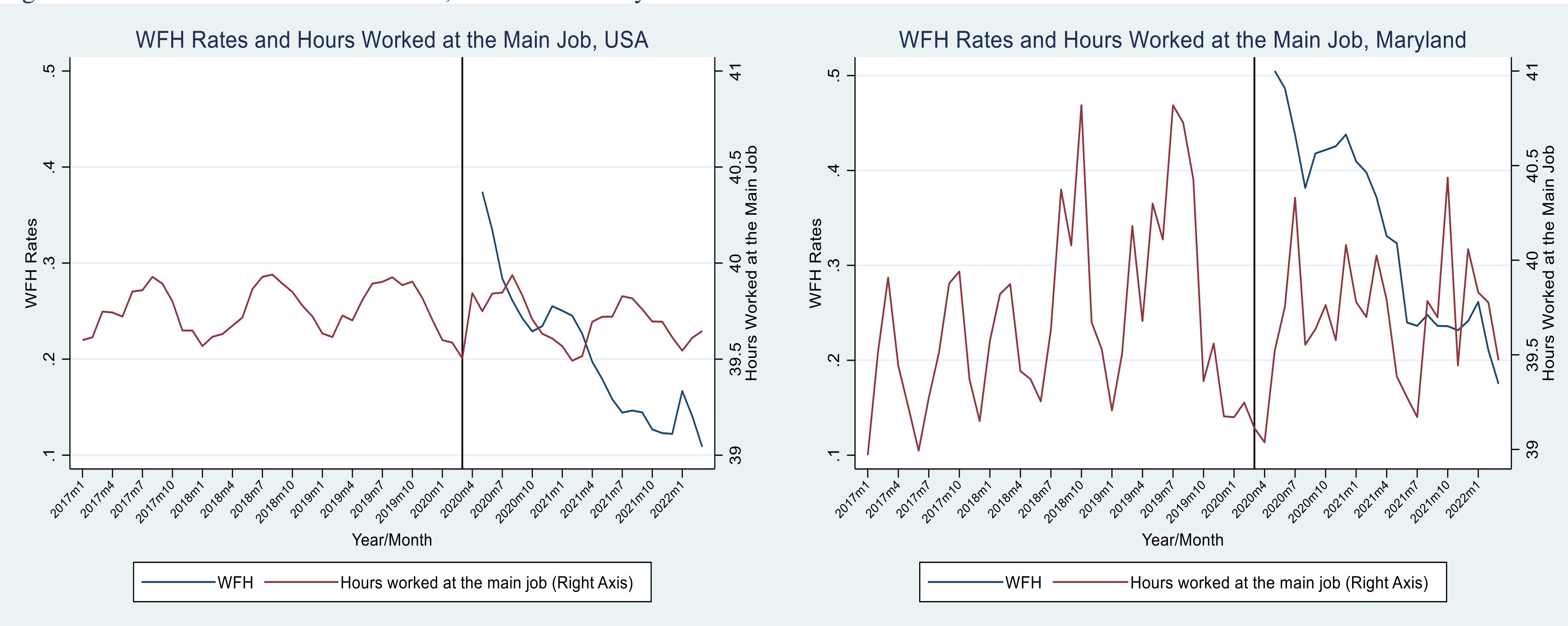
Maryland WFH Trends

With the raised popularity of WFH throughout the pandemic, the industry and occupation differences in WFH could be related to the changing industry and occupation mixes for Maryland economy. As Dingel & Neiman (2020) showed, WFH propensity varies by sectors. Zhang, et al. (2022) noted that this sectoral difference has varying impacts on business revenue, disruption insupply chains, closure, and cash flow.

Since the CPS data did not start collecting WFH data until the pandemic started, the monthly WFH trends in this study starts after the pandemic started in March 2020. As reflected in Figure 6, Maryland workers have a much higher WFH rate than the national average. With the lockdown ended and the improving pandemic situation, WFH rates dropped both for the United States and for Maryland.

Figure 6 also shows that the number of Maryland workers' working hours is slightly rising over time, including before the pandemic, while this is not the case for the United States as a whole. The longer working hours could partially explain the slower and not yet recovered employment in Maryland observed in Figure 1, but it could also be associated with the higher WFH rate in Maryland. Many WFH workers may feel the need to reciprocate the privilege of WFH in flexibility, autonomy, and saved commuting time by working longer hours and/or harder work (Gajendran & Harrison 2007). This mirrors longer reported working hours for WFH workers found by Kelliher & Anderson (2010) or the situation of hard to unplug work identified in a survey (Buffer 2019).

Figure 6. WFH Trends and Hours Worked, USA versus Maryland



Compared to the national average, Maryland workers are more likely to work from home in *Management* occupations *(SOC: 11)* and industry sectors of *Real Estate (NAICS: 53), Other Services (NAICS: 81), and Public Administration (NAICS: 92). Management occupations (SOC: 11) and industry sectors of Real Estate (NAICS: 53) and Public Administration (NAICS: 92)* are among the short list of Maryland sectors that grew from 2017 to 2022 reported in Figure 2.

Maryland workers work more hours than the national average in industry sectors of *Administrative Services (NAICS: 56), Education (NAICS: 61), Healthcare (NAICS: 62), Accommodation & Food Services (NAICS: 72), and Other Services (NAICS: 81)* and in occupation sectors of *Education & Library Services (SOC: 25), Arts, Design, Entertainment, Sports, and Media (SOC: 27), Food Preparation and Serving (SOC: 35), Building and Grounds Cleaning and Maintenance (SOC: 37),* and *Personal Care and Service (SOC: 39)*, but work fewer hours in occupation sectors of *Management (SOC: 11), Computer and Mathematics (SOC: 15), Architecture & Engineering (SOC: 17), Legal (SOC: 23), Protective Services (SOC: 33), Farming, Fishing, and Forestry (SOC: 45), Construction & Extraction (SOC: 47), Installation, Maintenance, and Repair (SOC: 49), and Transportation and Material Moving (SOC: 53)* occupations. This is reflected in Figure 7. Among this long list, only industry sectors of *Administrative Services (NAICS: 56)* and *Education (NAICS: 61*) and occupation sector *Education & Library Services (SOC: 25)* are among the short list of Maryland sectors with employment growth from 2017 to 2022. More hours worked from the incumbent workers could result in a lower demand for more workers.

Figure 8 shows that Maryland workers have higher earnings than average U.S. workers and WFH workers overall have higher earnings than non-WFH workers. WFH workers' higher earnings is reflected in Figure 9 in almost all industry and occupation sectors, except for industry sectors of *Management (NAICS: 55)* and *Utilities (NAICS: 22)* and occupation sectors of *Personal Care & Service (SOC: 39)* and *Construction & Extraction (SOC: 47)* in which earnings are similar between WFH and non-WFH workers. This pattern is similar for both United States as a whole and for Maryland[8].

[8] Compared to the United States as a whole, it seems that Maryland non-WFH workers in industry sector of *Management (NAICS: 55)* represented in this data show much lower earnings, but this is not the case in the occupation sector of *Management (SOC: 11)*. This could be related to limited number of observations in industry sector of *Management (SOC: 55)* in Maryland. Due to limited number of observations in Maryland in the CPS data, several sectors, such as industry sectors of *Mining (NAICS: 21)* and *Agriculture (NAICS; 11)* and occupation sectors of *Farming & Fishing (SOC: 45)* and *Building & Maintenance (SOC: 37)* have no representation in Maryland in the CPS data.

Figure 7 WFH Trends by NAICS Industry and SOC Occupation Sectors

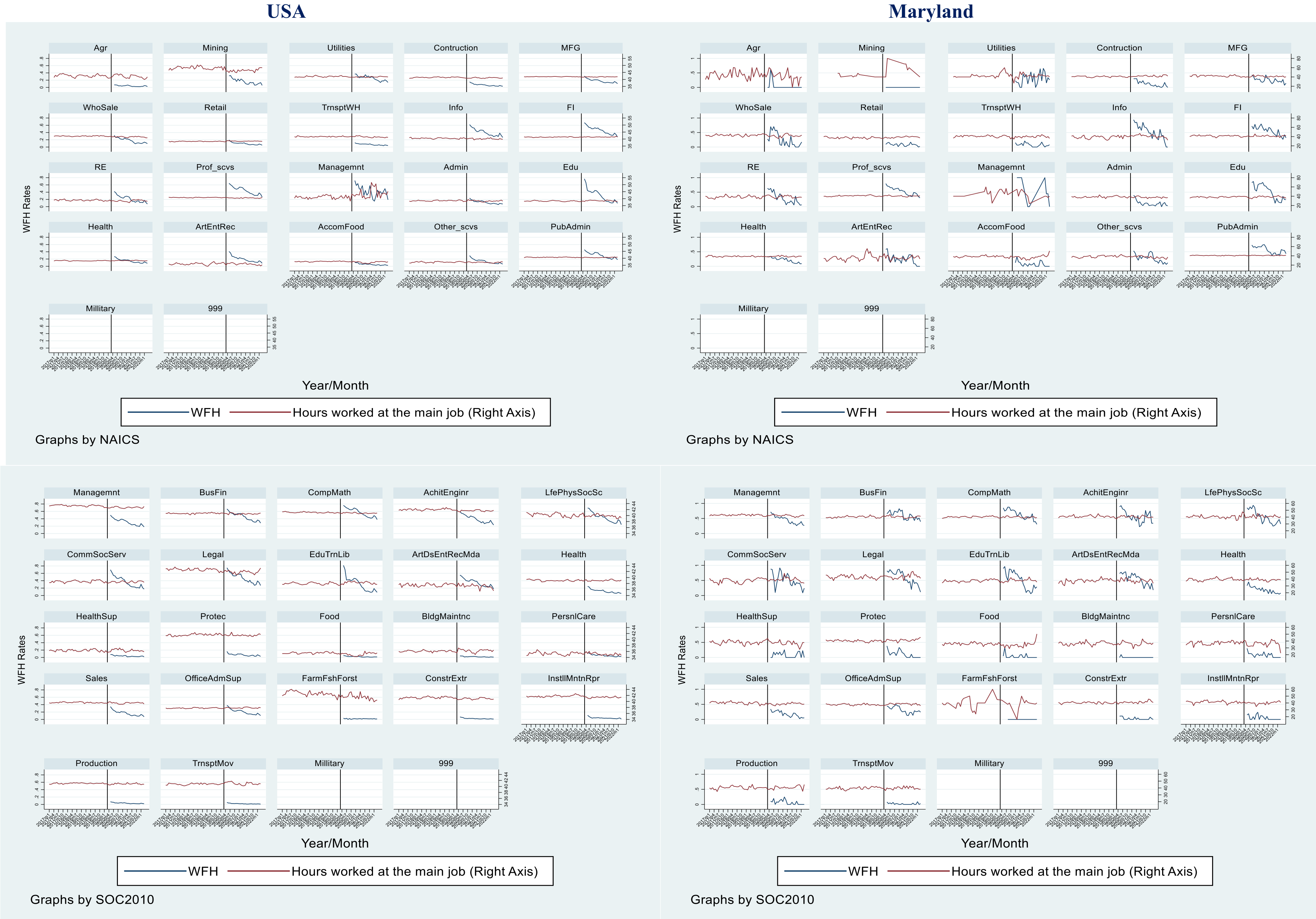


Figure 8. Median Weekly Earnings for WFH versus non-WFH Workers

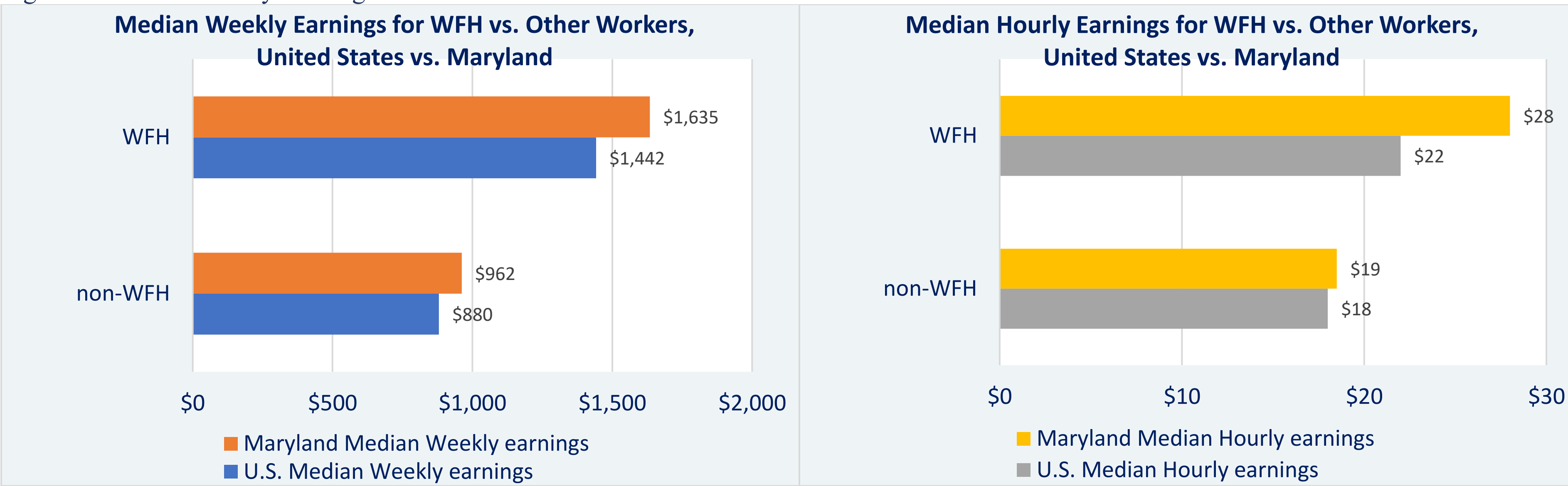
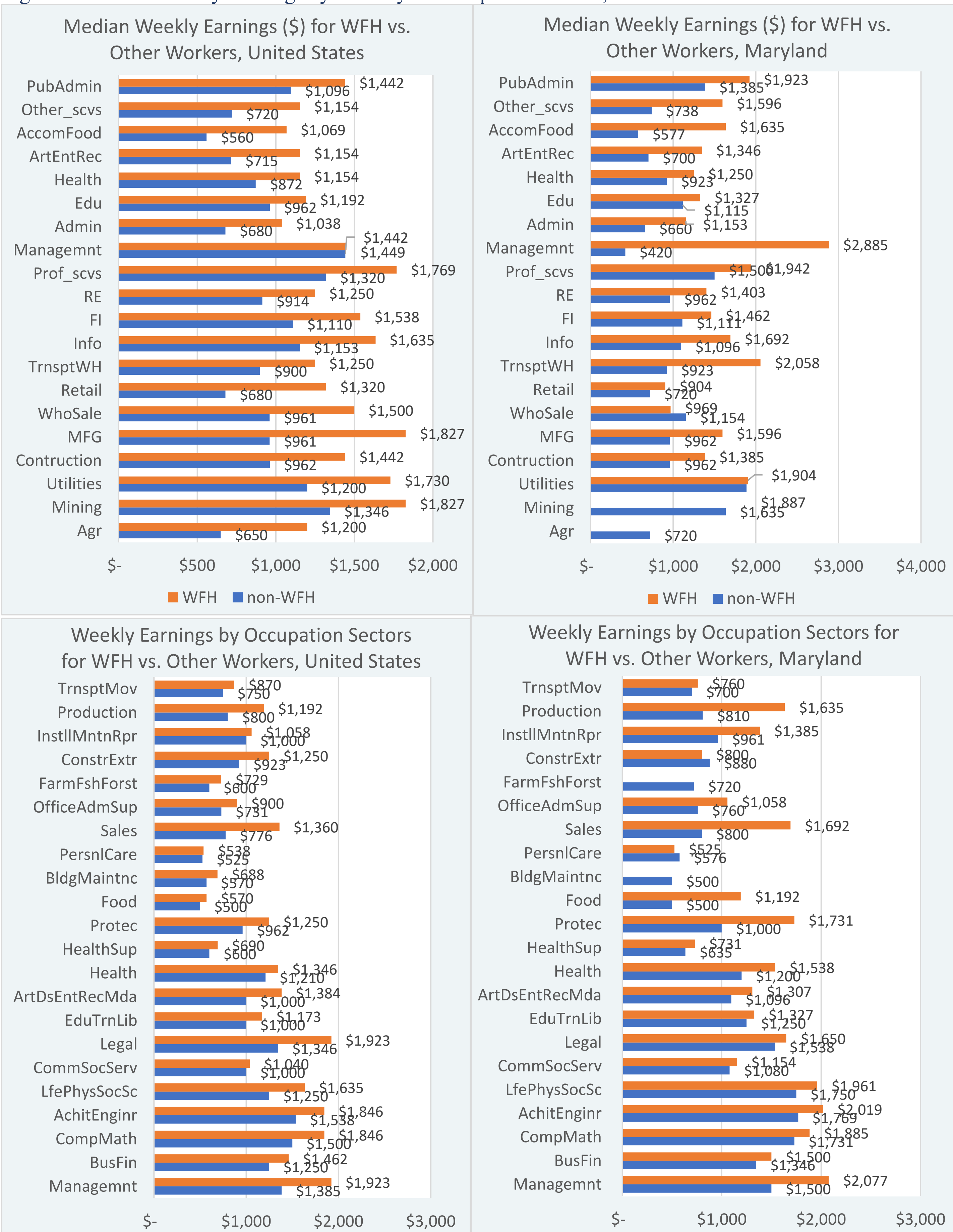


Figure 9. Median Weekly Earnings by Industry & Occupation Sectors, WFH versus. Non-WFH Jobs



Empirical Model Estimates: Factors Contributing to Self-Employment and WFH

This section of the study examines the factors affecting the self-employment trend and WFH trend in Maryland to understand who the self-employed or the WFH workers are and what sectors and locations are associated with the rise of self-employment and WFH in Maryland. This could have policy implications for Maryland's future workforce development system operations – such as entrepreneurship training, self-employment assistance, as well as WFH training and supports.

Table 1 presents the summary statistics for the variables across workers aged 25 and above in Maryland. Across the samples we observe in Maryland, 10% of the workers are *self-employment* and 90% are in *wage-and-salary employment*. Among the self-employed, 28% are *new* and 72% are *incumbent* self-employers, 44% are *incorporated* and 56% are *unincorporated* self-employers, 73% are *full-time* and 27% are *part-time* self-employers. Among all workers that we observe during the pandemic, 33% have WFH jobs and 67% have non-WFH jobs. The mean weekly earnings is $1,269, with a standard deviation at $791, ranging from $0.92 to $2,885. Among all observing Maryland workers of January 2017 through March 2022, 47% are male and 53% are female. For three age groups, 31% of the workers are young (ages of 41-61), 41% are middle aged (ages of 41-61), and 28% are post early retirement age (ages of 62-85). For racial distribution, 60% of the observing workers are White, 30% are African Americans, 8% are Asians, and 2% are of other or mixed races. For education attainment, 32% of the observing workers are educated up to high school level, 22% have some college education, 24% have Bachelor's degrees, and 21% have graduate school education. Fifty-six percent of the workers are married with spousal presence. Forty-four percent have children in the household. While only 16% of the workers have a family income less than $35,000 a year, 41% have family income ranging $35,000 to $99,000, and 44% have a family income of $100,000 or above. Almost all of the observed workers (96%) were employed in the prior month. The mean number of jobs the works have in the prior month is 0.71, ranging from 0 to 4. Among occupation sector distributions across the observed five years, *Management (SOC: 11)* and *Office and Administrative Support (SOC: 43)* Occupation sectors are the largest, take about respectively 15% and 10%; the rest occupation sectors each take about 0.2% in *Farming, Fishing, and Forestry Occupations (SOC: 43)* to 8% in *Sales and Related Occupations (SOC: 41)*. For industry sectors, 14% of observing workers in 2017-2022 work in *Professional Services (NAICS: 54)*, *Healthcare (NAICS: 62)* and *Public Administration (NAICS: 92)* each take 13%, 10% in *Education (NAICS: 61)*, and the rest industry sectors take from 0.1% in *Mining (NAICS: 21)* to 8% each in *Construction (NAICS: 23)* and *Retail Trade (NAICS: 44-45)*. Only civilian workers are observed. For the county distribution in the data, 36% of the observing workers did not specify which county they are from, 18% from Montgomery County, 15% from Prince George's County, 11% from Anne Arundel County, 9% from Baltimore City, 3% from Carroll County, 2% each from Cecil and Charles Counties. The observing period ranges from January 2017 to March 2022, with 40% of the observation in the COVID-19 pandemic.

Since many variables are modeled, correlation coefficients between variables were checked for potential multicollinearity concerns in our GEE population-averaged models. No correlation coefficient (presented in Appendix Tables A & B) is large enough to alarm of serious multicollinearity issues.

Table 1. Summary Statistics

Variable		Obs	Weight	Mean	Std. Dev.	Min	Max
Self-Employed (SE) vs. Wage & Salary Employment		43,532	180486517	**0.10**	0.30	0	1
New vs Incumbent SE		4,348	17457843	**0.28**	0.45	0	1
Incorporated vs. Unincorporated SE		4,348	17457843	**0.44**	0.50	0	1
Full-time vs. Part-time SE		4,229	16976423	**0.73**	0.44	0	1
WFH		13,199	60599930	**0.33**	0.47	0	1
Weekly Earnings		9,519	38691925	**1269**	791	0.92	2885
Male		63,571	258209952	**0.47**	0.50	0	1
AgeGr25							
	25-40	63,571	258209952	**0.31**	0.46	0	1
	41-61	63,571	258209952	**0.41**	0.49	0	1
	62-85	63,571	258209952	**0.28**	0.45	0	1
Race							
	White	63,571	258209952	**0.60**	0.49	0	1
	Black	63,571	258209952	**0.30**	0.46	0	1
	Asian PI	63,571	258209952	**0.08**	0.26	0	1
	Other	63,571	258209952	**0.02**	0.15	0	1
Educ							
	Up2HS	63,571	258209952	**0.32**	0.47	0	1
	Some College	63,571	258209952	**0.22**	0.42	0	1
	BSBA	63,571	258209952	**0.24**	0.43	0	1
	Grad School	63,571	258209952	**0.21**	0.41	0	1
Married Sp		63,571	258209952	**0.56**	0.50	0	1
Children in HH		63,571	258209952	**0.44**	0.50	0	1
Family Inc							
	<35k	63,571	258209952	**0.16**	0.36	0	1
	35-99k	63,571	258209952	**0.41**	0.49	0	1
	100k+	63,571	258209952	**0.44**	0.50	0	1
Employed Last Month		32,826	134969116	**0.96**	0.19	0	1
Num Jobs 5 Weeks Ago		48,491	195194208	**0.71**	0.55	0	4
SOC2010							
	Managemnt	43,532	180486517	**0.15**	0.36	0	1
	BusFin	43,532	180486517	0.07	0.25	0	1
	CompMath	43,532	180486517	0.06	0.24	0	1
	AchitEnginr	43,532	180486517	0.03	0.16	0	1
	LfePhysSo~c	43,532	180486517	0.02	0.15	0	1
	CommSocServ	43,532	180486517	0.02	0.14	0	1
	Legal	43,532	180486517	0.02	0.14	0	1
	EduTrnLib	43,532	180486517	0.07	0.25	0	1
	ArtDsEntR~a	43,532	180486517	0.02	0.15	0	1
	Health	43,532	180486517	0.06	0.25	0	1
	HealthSup	43,532	180486517	0.02	0.13	0	1
	Protec	43,532	180486517	0.03	0.16	0	1
	Food	43,532	180486517	0.03	0.18	0	1
	BldgMaintnc	43,532	180486517	0.03	0.18	0	1

	PersnlCare	43,532	180486517	0.03	0.18	0	1
	Sales	43,532	180486517	**0.08**	0.27	0	1
	OfficeAdm~p	43,532	180486517	**0.10**	0.31	0	1
	FarmFshFo~t	43,532	180486517	**0.002**	0.05	0	1
	ConstrExtr	43,532	180486517	0.05	0.22	0	1
	InstllMnt~r	43,532	180486517	0.02	0.15	0	1
	Production	43,532	180486517	0.02	0.15	0	1
	TrnsptMov	43,532	180486517	0.05	0.21	0	1
	Millitary	43,532	180486517	0.0000	0.01	0	1
NAICS							
	Agr	43,532	180486517	0.01	0.08	0	1
	Mining	43,532	180486517	**0.001**	0.03	0	1
	Utilities	43,532	180486517	0.01	0.09	0	1
	Contruction	43,532	180486517	**0.08**	0.27	0	1
	MFG	43,532	180486517	0.04	0.19	0	1
	WhoSale	43,532	180486517	0.02	0.13	0	1
	Retail	43,532	180486517	**0.08**	0.27	0	1
	TrnsptWH	43,532	180486517	0.04	0.19	0	1
	Info	43,532	180486517	0.02	0.13	0	1
	FI	43,532	180486517	0.04	0.19	0	1
	RE	43,532	180486517	0.02	0.15	0	1
	Prof_scvs	43,532	180486517	**0.14**	0.34	0	1
	Managemnt	43,532	180486517	0.00	0.03	0	1
	Admin	43,532	180486517	0.05	0.21	0	1
	Edu	43,532	180486517	**0.10**	0.30	0	1
	Health	43,532	180486517	**0.13**	0.34	0	1
	ArtEntRec	43,532	180486517	0.02	0.13	0	1
	AccomFood	43,532	180486517	0.05	0.21	0	1
	Other_scvs	43,532	180486517	0.05	0.21	0	1
	PubAdmin	43,532	180486517	**0.13**	0.33	0	1
	Military	43,532	180486517	0.00	0.01	0	1
County							
	Anne Arundel	63,571	258209952	**0.11**	0.31	0	1
	Carroll	63,571	258209952	**0.03**	0.16	0	1
	Cecil	63,571	258209952	**0.02**	0.13	0	1
	Charles	63,571	258209952	**0.02**	0.15	0	1
	Harford	63,571	258209952	**0.05**	0.21	0	1
	Montgomery	63,571	258209952	**0.18**	0.38	0	1
	Prince George’s	63,571	258209952	**0.15**	0.36	0	1
	Baltimore City	63,571	258209952	**0.09**	0.28	0	1
	Unspecified	63,571	258209952	**0.36**	0.48	0	1
COVID		63,571	258209952	**0.40**	0.49	0	1

Table 2 presents each contributing marginal effects for self-employment propensities from our GEE population-averaged logit models. According to Model (1), across 27,397 observations, male, older, or better educated workers are more likely to be *self-employed* instead of in *wage-and-salary* employment. Controlling for other variables and compared to the odds of being *wage-and-salary* workers, the odds of being self-employed for a male worker are 40% higher; moving up to an older age group among the age groups of 25-40, 41-61, and 62-85, the odds of being self-employed increased by 58%. There is no evident marginal race effect relative to White Americans on the odds of being *self-employed* (versus in *wage-and-salary* employment). Compared to those who attained up to high school level education, the odds for those with some college education to be *self-employed* (versus in *wage-and-salary* employment) is 27% higher and the odds with graduate school education is 32% higher, ceteris paribus. Compared to *Management (SOC: 11)* occupations, while *Arts, Design, Entertainment, Sports, and Media (SOC: 27)* and *Personal Care & Service (SOC: 39)* occupations have higher odds of being *self-employed* (versus in *wage-and-salary* employment), most other occupation sectors—*Computer & Mathematical(SOC: 15), Architecture & Engineering (SOC: 17), Community and Social Service (SOC: 21), Healthcare Practitioners & Technical (SOC: 29), Healthcare Support (SOC: 31), Protective Service (SOC: 33), Food Preparation and Serving Related (SOC: 35), Office and Administrative Support (SOC: 43), Farming, Fishing, and Forestry (SOC: 45), Installation, Maintenance, & Repair (SOC: 49), Production (SOC: 51), Transportation and Material Moving (SOC: 53)* occupations—have lower odds, ceteris paribus. Among industry sectors, *Agriculture (NAICS: 11)* has higher odds of being *self-employed* (versus in *wage-and-salary* employment) than all other sectors with enough observations. No evident marginal differences across counties were observed for the odds of being *self-employed* (versus in *wage-and-salary* employment). Most industry and occupation sectors that have employment growth in Maryland from 2017-2022 reported in Figure 2 have the lowest odds of being self-employed (versus in wage-and-salary employment), including industry sectors of *Education (NAICS: 61)*, *Administrative Services (NAICS: 56)*, *Management (NAICS: 55)*, *Real Estate (NAICS:53), Manufacturing (NAICS:31-33)*, *Mining (NAICS: 21)*, *Finance & Insurance (NAICS:52)* and occupation sector *Healthcare Support occupations (SOC: 31).* Self-employment could be an alternative to wage-and-salary employment. Although in the CPS data, self-employment is included in the total employment, sectors with high self-employment, particularly unincorporated solo self-employment could signal a tight labor market.

Models (2) through (4) estimate marginal variable effects on specific self-employment type propensities: to be in respectively *new* (versus *incumbent*), or *incorporated* (versus *unincorporated*), or *full-time* (versus *part-time*) self-employment. Controlling for other variables, male self-employed workers are more likely to be *new* (versus *incumbent*), *incorporated* (versus *unincorporated*), and *full-time* (versus *part-time*) self-employers; this is consistent with the literature (e.g., Zhang et al 2018). Ceteris paribus, younger, African (versus White American), Cecil (versus unspecified) County self-employed workers are more likely to be *new* or *full-time* (versus respectively *incumbent* or *part-time*) self-employers; higher education attainment is associated with higher odds of being *incorporated* (versus *unincorporated*) and *part-time* (versus *full-time*) self-employment; being married with spouse's presence is associated with higher odds of being *incorporated* (versus *unincorporated*) but *incumbent* (versus *new*) self-employment; higher family income is associated with higher odds of being *full-time* (versus *part-time*) self-employment; being employed in the previous month is more likely to be associated with *incumbent* (versus *new*) self-employment in the current month; having more jobs in the previous month is more likely to be associated with *incorporated* (versus *unincorporated* self-employment. Compared to *Management (SOC: 11)* occupations and controlling for other variables, *Life, Physical, & Social Science (SOC: 19)* and *Food Preparation & Serving Related (SOC: 35)* occupations are more likely to be associated with *part-time* (versus *full-time*) self-employment, the odds of being *new* (versus *incumbent*) self-employers in *Healthcare Support (31)* are 7.55 times of that in *Management (SOC: 11)* occupations; *Building and Grounds Cleaning and Maintenance (SOC: 37)* occupations have higher odds than *Management (SOC: 11)* occupations to be *unincorporated* (versus *incorporated*) self-employers; *Office & Administrative Support* occupations *(SOC: 43)* are three times as likely to be *new* (versus *incumbent*) self-employers, but 61% less likely to be *full-time* (versus *part-time*) self-employers, compared to *Management occupations (SOC: 11)*; *Construction and Extraction occupations (SOC: 47)* are twice as likely as *Management occupations (SOC: 11)* to be *new* (versus *incumbent*) self-employers; *Installation, Maintenance, and Repair occupations (SOC: 49)* are 3.7 times as likely to be *full-time* (versus *part-time*) self-employers, but 56% less likely to be *incorporated* (versus *unincorporated*) self-employers, relatively to *Management (SOC: 11) occupations*; *Transportation and*

Material Moving occupations (SOC: 53) are 3.5 times as likely to be *new* (versus *incumbent*) self-employers, but 69% less likely to be *incorporated* (versus *unincorporated*) self-employers. The high odds of *incorporated* (versus *unincorporated*) self-employment to be in *Management (SOC: 11)* (versus other) occupations and the high odds in *Healthcare Support (SOC: 31)* (versus *Management*) occupations (at 7.55 times) are related to employment growth in those two occupation sectors reported in Figure 2. *New* self-employers themselves contribute to the total employment and *incorporated* self-employment and *new* businesses also often create jobs for more employees. *Incorporated* self-employment typically run larger businesses (Glover & Short, 2009), with a greater likelihood of having paid employees (Hipple & Hammond, 2016) than *unincorporated* self-employment.

Table 2. GEE Population-Averaged Logit Models for Self-Employment Propensities

	Model (1): SE vs. WS			**Model (2): New vs. Existing SE**			**Model (3): Incorporated vs. Unincorporated SE**			**Model (4): Full-time vs. Part-time SE**		
	Odds Ratio	***Robust Std. Err.***		**Odds Ratio**	***Robust Std. Err.***		**Odds Ratio**	***Robust Std. Err.***		**Odds Ratio**	***Robust Std. Err.***	
Male	1.40	*(0.14)*	***	1.90	*(0.41)*	***	1.49	*(0.25)*	**	2.56	*(0.43)*	***
AgeGr25	1.58	*(0.1)*	***	0.76	*(0.1)*	**	0.99	*(0.14)*		0.68	*(0.08)*	***
Race: Black vs. White	0.93	*(0.11)*		1.82	*(0.42)*	***	1.02	*(0.2)*		1.80	*(0.37)*	***
Race: Asian PI vs. White	1.05	*(0.17)*		1.79	*(0.55)*	*	1.29	*(0.38)*		1.13	*(0.29)*	
Race: Other vs. White	1.06	*(0.23)*		1.07	*(0.7)*		2.06	*(1.02)*		1.53	*(0.9)*	
Educ: Some College vs. Up2HS	1.27	*(0.12)*	***	0.65	*(0.15)*	*	1.55	*(0.23)*	***	0.72	*(0.14)*	*
Educ: BSBA vs. Up2HS	1.00	*(0.14)*		0.65	*(0.17)*	*	1.69	*(0.32)*	***	0.66	*(0.14)*	**
Educ: Grad School vs. Up2HS	1.32	*(0.2)*	*	0.92	*(0.29)*		3.59	*(0.94)*	***	1.00	*(0.25)*	
Married Sp	1.13	*(0.14)*		0.56	*(0.11)*	***	1.66	*(0.33)*	***	1.10	*(0.17)*	
Children in HH	1.15	*(0.12)*		1.14	*(0.22)*		0.71	*(0.13)*	*	1.05	*(0.15)*	
Fam Inc	1.00	*(0.07)*		1.13	*(0.16)*		0.89	*(0.11)*		1.23	*(0.12)*	**
Employed Last Moth	1.17	*(0.17)*		0.09	*(0.04)*	***	0.86	*(0.22)*		1.93	*(1.12)*	
Num Jobs 5 w ago	1.08	*(0.08)*		1.33	*(0.35)*		1.26	*(0.13)*	**	1.24	*(0.17)*	
SOC: BusFin vs. Mgmt.	0.97	*(0.15)*		2.13	*(0.89)*	*	1.12	*(0.36)*		0.67	*(0.16)*	*
SOC: CompMath vs. Mgmt.	0.54	*(0.1)*	***	1.55	*(0.86)*		1.12	*(0.35)*		0.78	*(0.28)*	
SOC: AchitEnginr vs. Mgmt.	0.27	*(0.13)*	***	1.32	*(1.42)*		1.34	*(0.77)*		1.31	*(0.57)*	
SOC: LfePhysSocSc vs. Mgmt.	0.73	*(0.23)*		0.41	*(0.3)*		0.63	*(0.2)*		0.33	*(0.12)*	***
SOC: CommSocServ vs. Mgmt.	0.21	*(0.15)*	**	2.73	*(2.39)*		0.46	*(0.2)*	*	0.55	*(0.33)*	
SOC: Legal vs. Mgmt.	1.03	*(0.2)*		0.22	*(0.23)*		1.46	*(0.45)*		1.01	*(0.45)*	
SOC: EduTrnLib vs. Mgmt.	0.63	*(0.24)*		0.67	*(0.54)*		0.61	*(0.96)*		0.63	*(0.25)*	
SOC: ArtDEnRecMda vs. Mgmt.	1.75	*(0.4)*	**	1.44	*(0.69)*		1.08	*(0.42)*		1.46	*(0.38)*	
SOC: Health vs. Mgmt.	0.47	*(0.13)*	***	1.23	*(0.74)*		0.61	*(0.22)*		0.87	*(0.3)*	
SOC: HealthSup vs. Mgmt.	0.35	*(0.17)*	**	7.55	*(6.4)*	**	0.49	*(0.41)*		1.21	*(0.98)*	
SOC: Protec vs. Mgmt.	0.17	*(0.06)*	***	1.00	*(empty)*		0.74	*(1.09)*		0.19	*(0.33)*	
SOC: Food vs. Mgmt.	0.45	*(0.12)*	***	2.34	*(1.78)*		0.40	*(0.35)*		0.31	*(0.18)*	**
SOC: BldgMaintnc vs. Mgmt.	0.74	*(0.17)*		1.93	*(1.33)*		0.34	*(0.17)*	**	1.04	*(0.42)*	
SOC: PersnlCare vs. Mgmt.	1.53	*(0.39)*	*	1.79	*(0.81)*		0.48	*(0.27)*		1.82	*(0.69)*	
SOC: Sales vs. Mgmt.	1.04	*(0.16)*		1.26	*(0.53)*		1.23	*(0.4)*		1.03	*(0.26)*	
SOC: OfficeAdmSup vs. Mgmt.	0.30	*(0.06)*	***	3.08	*(1.66)*	**	0.73	*(0.31)*		0.39	*(0.12)*	***
SOC: FarmFshForst vs. Mgmt.	0.28	*(0.21)*	*	1.75	*(1.66)*		1.00	*(empty)*		1.34	*(1.04)*	

SOC: ConstrExtr vs. Mgmt.	0.80	*(0.18)*		2.07	*(0.77)*	**	0.69	*(0.28)*		0.72	*(0.17)*	
SOC: InstllMntnRpr vs. Mgmt.	0.54	*(0.12)*	***	2.45	*(1.67)*		0.44	*(0.2)*	*	3.73	*(1.61)*	***
SOC: Production vs. Mgmt.	0.47	*(0.15)*	**	1.71	*(1.39)*		0.80	*(0.38)*		1.65	*(0.87)*	
SOC: TrnsptMov vs. Mgmt.	0.59	*(0.13)*	**	3.49	*(2.63)*	*	0.31	*(0.19)*	**	0.63	*(0.24)*	
NAICS: Contruction vs. Agr.	0.24	*(0.13)*	***	0.83	*(0.68)*		1.04	*(0.65)*		1.42	*(0.71)*	
NAICS: MFG vs. Agr.	0.09	*(0.05)*	***	0.74	*(0.77)*		0.91	*(0.62)*		2.26	*(1.54)*	
NAICS: WhoSale vs. Agr.	0.13	*(0.08)*	***	1.63	*(1.76)*		0.77	*(0.51)*		1.48	*(0.89)*	
NAICS: Retail vs. Agr.	0.14	*(0.08)*	***	0.98	*(0.9)*		0.61	*(0.4)*		1.02	*(0.55)*	
NAICS: TrnsptWH vs. Agr.	0.30	*(0.17)*	**	0.31	*(0.4)*		1.36	*(0.98)*		1.47	*(0.87)*	
NAICS: Info vs. Agr.	0.09	*(0.05)*	***	0.58	*(0.77)*		1.32	*(1.5)*		0.26	*(0.19)*	*
NAICS: FI vs. Agr.	0.11	*(0.07)*	***	1.69	*(1.57)*		0.44	*(0.34)*		1.18	*(0.79)*	
NAICS: RE vs. Agr.	0.28	*(0.16)*	**	1.47	*(1.3)*		1.10	*(0.77)*		1.18	*(0.66)*	
NAICS: Prof_scvs vs. Agr.	0.18	*(0.1)*	***	0.97	*(0.83)*		0.42	*(0.26)*		0.81	*(0.38)*	
NAICS: Managemnt vs. Agr.	0.13	*(0.09)*	***	1.00	*(empty)*		1.00	*(empty)*		1.00	*(empty)*	
NAICS: Admin vs. Agr.	0.25	*(0.14)*	**	0.50	*(0.54)*		0.98	*(0.68)*		1.04	*(0.57)*	
NAICS: Edu vs. Agr.	0.05	*(0.03)*	***	3.25	*(3.17)*		0.30	*(0.37)*		0.76	*(0.5)*	
NAICS: Health vs. Agr.	0.12	*(0.07)*	***	1.40	*(1.19)*		0.99	*(0.74)*		1.90	*(1.03)*	
NAICS: ArtEntRec vs. Agr.	0.21	*(0.13)*	**	0.71	*(0.67)*		0.37	*(0.26)*		0.30	*(0.16)*	**
NAICS: AccomFood vs. Agr.	0.12	*(0.07)*	***	2.11	*(2.07)*		1.55	*(1.3)*		1.29	*(0.9)*	
NAICS: Other_scvs vs. Agr.	0.13	*(0.08)*	***	0.60	*(0.55)*		1.15	*(0.76)*		0.34	*(0.19)*	*
NAICS: PubAdmin vs. Agr.	1.00	*(empty)*										
County: Carroll vs. Unspec.	1.09	*(0.28)*		0.75	*(0.46)*		1.57	*(0.65)*		0.79	*(0.36)*	
County: Cecil vs. Unspec.	1.03	*(0.39)*		5.13	*(2.62)*	***	1.58	*(0.92)*		12.49	*(14.87)*	**
County: Charles vs. Unspec.	0.79	*(0.31)*		0.81	*(0.61)*		0.29	*(0.22)*		1.08	*(0.71)*	
County: Harford vs. Unspec.	0.89	*(0.22)*		1.52	*(0.7)*		0.67	*(0.27)*		1.17	*(0.54)*	
County: Montgomery vs. Unspec.	1.05	*(0.17)*		0.70	*(0.24)*		1.07	*(0.28)*		0.78	*(0.21)*	
County: Prince George's vs. Unspec.	0.79	*(0.14)*		1.25	*(0.47)*		0.72	*(0.23)*		0.62	*(0.2)*	
County: Baltimore City vs. Unspec.	1.15	*(0.22)*		0.99	*(0.43)*		0.85	*(0.31)*		0.95	*(0.37)*	
County: Other vs. Unspec.	1.20	*(0.16)*		1.02	*(0.32)*		0.86	*(0.21)*		1.02	*(0.26)*	
COVID	0.96	*(0.09)*		0.58	*(0.21)*		0.72	*(0.13)*	*	0.65	*(0.11)*	**
Year Month	1.00	*(0)*		1.01	*(0.01)*		1.01	*(0.01)*	*	1.01	*(0.01)*	
_cons	0.48	*(1)*		0.00	*(0)*		0.00	*(0)*	*	0.00	*(0.02)*	
Number of obs	27397			3159			3154			3096		
Number of groups	7114			965			964			941		
min	1			1			1			1		
avg	4			3			3			3		
max	7			7			7			7		
Wald chi2(64)	379		***	164		***	109		***	175		***

Notes:

1) Stand errors adjusted for clustering on each individual person are presented in italic format in parentheses.
2) Significance level at 0.01 is denoted with ***, at 0.05 is denoted with **, and at 0.1 is denoted with *.

Model (5) in Table 3 presents each variable's odds ratio to be associated with *WFH* (versus *non-WFH*) jobs since the pandemic started. Controlling for all other variables, female and better educated workers with higher family income are more likely to work from home; male workers have odds that are 14% lower than female workers to have a WFH job; workers with some college education, Bachelor's Degree, and Graduate School education attainments have odds that are respectively 1.53, 2.47, and 3.48 times of that for those with only up to high school education attainments; when family income increased from less than $35,000 to $35,000-$99,000, or from $35,000-$99,000 to $100,000 and above, the odds to work from home increased by 50% in each case. Compared to *Management (SOC: 11)* occupations and holding all other variables constant, *Business & Financial Operations (SOC: 13)* and *Computer & Mathematical Occupations (SOC: 15)* are more likely to work from home, while many other sectors—*Education, Training, & Library (SOC: 25), Healthcare Practitioners & Technical (SOC: 29), Healthcare Support Occupations (SOC: 31), Protective Service (SOC: 33), Food Preparation & Serving Related occupations (SOC: 35), Personal Care & Service (SOC: 39), Sales & Related (SOC: 41), Construction & Extraction (SOC: 47), Installation, Maintenance, & Repair (SOC: 49), Production (SOC: 51),* and *Transportation & Material Moving (SOC: 53)* occupations—are less likely to work from home. Relative to *Agriculture (NAICS:11)* industry sector, many NAICS-coded industry sectors have higher WFH odds: *Utilities (NAICS:22)* is 5.8 times, *Manufacturing (NAICS:31-33)* is 3.8 times, *Information (NAICS:51)* is 5.2 times, *Finance & Insurance (NAICS:52)* is 6.5 times, *Real Estate (53)* is 3.1 times, *Professional Services (NAICS:54)* is 4 times, *Administrative Services (NAICS:56)* is 3.2 times, *Education (NAICS:61)* is 5.6 times, *Healthcare (NAICS:62)* is 2.7 times, *Other Services (NAICS:81)* is 3.9 times, and *Public Administration (NAICS:92)* is 8.8 times of that for *Agriculture (NAICS:11)*, ceteris paribus. Compared to observations with unspecified county locations, the WFH odds for *Harford County* residents is 76% lower, but for *Montgomery, Prince George's,* and *Baltimore City* are respectively 61%, 53%, and 74% higher, ceteris paribus.

Table 3. GEE Population-Averaged Logit Models for WFH Propensities

	Model (5): WFH vs. non-WFH Jobs		
	Odds Ratio	***Robust Std. Err.***	
Male	0.86	*(0.08)*	*
AgeGr25	0.96	*(0.06)*	
Race: Black vs. White	0.97	*(0.11)*	
Race: Asian PI vs. White	1.07	*(0.15)*	
Race: Other vs. White	1.26	*(0.41)*	
Educ: Some College vs. Up2HS	1.53	*(0.22)*	***
Educ: BSBA vs. Up2HS	2.47	*(0.34)*	***
Educ: Grad School vs. Up2HS	3.48	*(0.5)*	***
Married Sp	1.02	*(0.1)*	
Children in HH	0.93	*(0.08)*	
Fam Inc	1.50	*(0.11)*	***
Employed Last Moth	1.16	*(0.31)*	
Num Jobs 5 w ago	1.06	*(0.11)*	
SOC: BusFin vs. Management	1.40	*(0.21)*	**
SOC: CompMath vs. Management	1.55	*(0.25)*	***
SOC: AchitEnginr vs. Management	1.29	*(0.29)*	
SOC: LfePhysSocSc vs. Management	0.76	*(0.17)*	
SOC: CommSocServ vs. Management	1.46	*(0.41)*	
SOC: Legal vs. Management	0.87	*(0.2)*	
SOC: EduTrnLib vs. Management	0.70	*(0.13)*	*

SOC: ArtDsEntRecMda vs. Management	1.36	(0.32)	
SOC: Health vs. Management	0.29	(0.06)	***
SOC: HealthSup vs. Management	0.16	(0.07)	***
SOC: Protec vs. Management	0.12	(0.04)	***
SOC: Food vs. Management	0.17	(0.09)	***
SOC: BldgMaintnc vs. Management	1.00	(empty)	
SOC: PersnlCare vs. Management	0.18	(0.08)	***
SOC: Sales vs. Management	0.54	(0.11)	***
SOC: OfficeAdmSup vs. Management	0.81	(0.12)	
SOC: FarmFshForst vs. Management	1.00	(empty)	
SOC: ConstrExtr vs. Management	0.12	(0.07)	***
SOC: InstllMntnRpr vs. Management	0.15	(0.06)	***
SOC: Production vs. Management	0.17	(0.06)	***
SOC: TrnsptMov vs. Management	0.08	(0.04)	***
NAICS: Mining vs. Agriculture	1.00	(empty)	
NAICS: Utilities vs. Agriculture	5.75	(4.17)	**
NAICS: Contruction vs. Agriculture	1.73	(0.99)	
NAICS: MFG vs. Agriculture	3.82	(2.22)	**
NAICS: WhoSale vs. Agriculture	2.26	(1.37)	
NAICS: Retail vs. Agriculture	1.01	(0.61)	
NAICS: TrnsptWH vs. Agriculture	1.37	(0.86)	
NAICS: Info vs. Agriculture	5.22	(3.11)	***
NAICS: FI vs. Agriculture	6.52	(3.66)	***
NAICS: RE vs. Agriculture	3.13	(1.85)	*
NAICS: Prof_scvs vs. Agriculture	4.05	(2.19)	***
NAICS: Managemnt vs. Agriculture	3.34	(3.74)	
NAICS: Admin vs. Agriculture	3.16	(1.87)	*
NAICS: Edu vs. Agriculture	5.62	(3.21)	***
NAICS: Health vs. Agriculture	2.73	(1.51)	*
NAICS: ArtEntRec vs. Agriculture	2.40	(1.6)	
NAICS: AccomFood vs. Agriculture	1.42	(0.87)	
NAICS: Other_scvs vs. Agriculture	3.88	(2.24)	**
NAICS: PubAdmin vs. Agriculture	8.80	(4.83)	***
County: Carroll vs. Unspecified	1.04	(0.27)	
County: Cecil vs. Unspecified	0.95	(0.35)	
County: Charles vs. Unspecified	1.44	(0.39)	
County: Harford vs. Unspecified	0.24	(0.07)	***
County: Montgomery vs. Unspecified	1.61	(0.24)	***
County: Prince George's vs. Unspecified	1.53	(0.26)	**
County: Baltimore City vs. Unspecified	1.74	(0.35)	***
County: Othel vs. Unspecified	1.04	(0.15)	
COVID	1.00	(omitted)	
Year Month	0.90	(0.01)	***
_cons	1.7E+31	(6.83E+31)	***
Number of obs	9716		
Number of groups	3075		
min	1		
avg	3		

max	7	
Wald chi2(64)	1079	***

Notes:

1) Stand errors adjusted for clustering on each individual person are presented in italic format in parentheses.
2) Significance level at 0.01 is denoted with ***, at 0.05 is denoted with **, and at 0.1 is denoted with *.

Model (6) in Table 4 presents the marginal estimates on weekly earnings. We modeled on weekly earnings only to make the best use of the CPS data, considering that many more people reported weekly earnings than hourly earnings in the CPS data, hourly earnings could be limited to hourly wage jobs, and the number of observations across occupational and industry sectors for hourly earnings are very low.

Holding all other variables constant, WFH jobs are paid averagely $144 more each week than non-WFH jobs during the pandemic. male workers are paid $240 more weekly; compared to White Americans, African Americans are paid respectively $100 less; older, better educated workers, or in households with children or with higher family income, those who were employed in the prior month are paid more weekly. Compared to *Management (SOC: 11)* occupations, most occupations are paid much less weekly, ranging from $169 less in *Healthcare Practitioners and Technical occupations (SOC: 29)* to $914 less in *Farming, Fishing, and Forestry Occupations (SOC: 45)*. Only in *Computer & Mathematical (SOC: 15)*, Architecture & *Engineering (SOC: 17),* and *Life, Physical, & Social Science (SOC:19)* occupations, there is no statistically significant differences between those occupations and *Management (SOC: 11)* occupations. Compared to *Agriculture (NAICS: 11)* jobs, jobs in industry sectors of *Administrative Services (NAICS:56), Education (NAICS: 61), and other Services (NAICS: 81)* are paid less, ceteris paribus. Compared to individuals who did not report county locations, weekly earnings for residents from *Harford County* and *Montgomery County* are paid respectively $223 and $127 lower; however, those with unspecified county information take 36% of the sample (as shown in Table 1) and could come from anywhere and thus this comparison is not really meaningful. Please note since WFH is only measured in the pandemic, Model (6) only tests the observations in the pandemic. Table 4 shows more details by each sector. Please note that due to insufficient number of observations with earnings information among self-employed workers, we could not model earnings differences comparing between self-employed workers and others.

Table 4. GEE Population-Averaged Models for Weekly Earnings

	Model (6): Weekly Earnings		
	Coef.	Robust Std. Err.	
WFH	144.22	(32.83)	***
Male	240.20	(29.52)	***
AgeGr25	110.30	(19.22)	***
Race: Black vs. White	-100.43	(33.11)	***
Race: Asian PI vs. White	-56.81	(48.32)	
Race: Other vs. White	-12.83	(74.45)	
Educ: Some College vs. Up2HS	7.08	(33.39)	
Educ: BSBA vs. Up2HS	277.28	(40.5)	***
Educ: Grad School vs. Up2HS	536.71	(46.45)	***
Married Sp	47.12	(30.2)	
Children in HH	117.46	(27.28)	***
Fam Inc	218.18	(23.06)	***
Employed Last Moth	449.74	(99.25)	***
Num Jobs 5 w ago	-68.33	(47.16)	
SOC: BusFin vs. Management	-216.45	(60.89)	***
SOC: CompMath vs. Management	-34.80	(60.3)	
SOC: AchitEnginr vs. Management	-102.54	(87.29)	
SOC: LfePhysSocSc vs. Management	-82.87	(78.3)	
SOC: CommSocServ vs. Management	-198.91	(87.94)	**
SOC: Legal vs. Management	-390.21	(98.03)	***
SOC: EduTrnLib vs. Management	-277.63	(76.91)	***
SOC: ArtDsEntRecMda vs. Management	-347.58	(96.16)	***
SOC: Health vs. Management	-168.60	(68.93)	**
SOC: HealthSup vs. Management	-394.07	(73.3)	***
SOC: Protec vs. Management	-327.14	(86.07)	***
SOC: Food vs. Management	-498.46	(94.95)	***
SOC: BldgMaintnc vs. Management	-349.46	(123.04)	***
SOC: PersnlCare vs. Management	-534.41	(84.73)	***
SOC: Sales vs. Management	-223.60	(80.43)	***
SOC: OfficeAdmSup vs. Management	-415.07	(50.65)	***
SOC: FarmFshForst vs. Management	-914.38	(212.05)	***
SOC: ConstrExtr vs. Management	-381.28	(80.39)	***
SOC: InstllMntnRpr vs. Management	-337.25	(80.51)	***
SOC: Production vs. Management	-387.35	(82.93)	***
SOC: TrnsptMov vs. Management	-434.50	(62.46)	***
NAICS: Mining vs. Agriculture	470.60	(431.1)	
NAICS: Utilities vs. Agriculture	53.73	(242.09)	
NAICS: Contruction vs. Agriculture	-240.22	(189.53)	
NAICS: MFG vs. Agriculture	-175.55	(187.27)	
NAICS: WhoSale vs. Agriculture	-73.46	(198.3)	
NAICS: Retail vs. Agriculture	-304.81	(188.42)	
NAICS: TrnsptWH vs. Agriculture	-165.78	(186.8)	
NAICS: Info vs. Agriculture	-75.39	(204.88)	
NAICS: FI vs. Agriculture	-138.08	(189.92)	

NAICS: RE vs. Agriculture	-218.65	*(207.03)*	
NAICS: Prof_scvs vs. Agriculture	-71.67	*(182.35)*	
NAICS: Managemnt vs. Agriculture	241.45	*(338.58)*	
NAICS: Admin vs. Agriculture	-351.33	*(190.44)*	*
NAICS: Edu vs. Agriculture	-425.52	*(188.35)*	**
NAICS: Health vs. Agriculture	-288.56	*(184.09)*	
NAICS: ArtEntRec vs. Agriculture	-313.20	*(209.43)*	
NAICS: AccomFood vs. Agriculture	-266.59	*(180.83)*	
NAICS: Other_scvs vs. Agriculture	-346.76	*(188.14)*	*
NAICS: PubAdmin vs. Agriculture	-34.00	*(183.66)*	
County: Carroll vs. Unspecified	-40.57	*(80.63)*	
County: Cecil vs. Unspecified	-46.61	*(105.42)*	
County: Charles vs. Unspecified	-124.87	*(80.19)*	
County: Harford vs. Unspecified	-222.81	*(67.05)*	***
County: Montgomery vs. Unspecified	-126.95	*(50.47)*	**
County: Prince George's vs. Unspecified	1.14	*(55.03)*	
County: Baltimore City vs. Unspecified	-53.28	*(56.97)*	
County: Other vs. Unspecified	-55.66	*(43.87)*	
COVID	0.00	*(omitted)*	***
Year Month	4.47	*(1.8)*	**
_cons	-2957.09	*(1339.97)*	**
Number of obs	2320.00		
Number of groups	1.00		
min	1.20		
avg	2.00		
max	2400.23		***
Wald chi2(64)	0.00		

Notes:

1) Stand errors adjusted for clustering on each individual person are presented in italic format in parentheses.
2) Significance level at 0.01 is denoted with ***, at 0.05 is denoted with **, and at 0.1 is denoted with *.

All models explained the variability of our dependent variables. All models have statistically highly significant ($p<0.001$) Wald test statistics, rejecting the null hypothesis that all the coefficients in the model are simultaneously zero. The main model estimates are also consistent with multilevel mixed-effects (hierarchical) models. This demonstrates our model robustness.

Discussion and Conclusion

Relying on the monthly individual level Current Population Survey (CPS) Data of civilians aged 25 or above and multiple generalized estimating equation (GEE) population-averaged models, this study first identifies a slower employment recovery in Maryland than the national average two years after the pandemic started and notes Maryland industry and occupation mixes have changed from 2017 to 2020. Only few sectors grew. Maryland's top two typical industry sectors*, Health Care & Social Assistance (NAICS:62)* and *Professional Services (NAICS:54)*, are both shrinking, while *Public Administration (NAICS:92)* and *Education (NAICS:61)* emerged to the top in March 2022.

One major economic trend is the rise of self-employment, though Maryland has a similar *self-employment* (versus *wage-and-salary employment*) rate to the national average. However, Maryland has a higher *incorporated* (versus *unincorporated*) self-employment rate, particularly after the COVID-19 pandemic started. Compared to *unincorporated* entrepreneurs, *incorporated* entrepreneurs earn more (Levine & Rubinstein, 2013), have higher levels of education, experience, and resources (Light & Munk, 2015), and run larger businesses (Glover & Short, 2009), with a greater likelihood of having paid employees (Hipple & Hammond, 2016). Specializing in *incorporated* (versus *unincorporated*) self-employment therefore helps boost local economy. This shows a hope for Maryland's slower recovery. The empirical models in this study also show that male, better educated self-employers, with more jobs in the prior month, in *Management (SOC: 11) occupations* (versus *Transportation and Material Moving occupations (SOC: 53)* are more likely to be in *incorporated* (versus *unincorporated*) self-employment.

This study identifies targeted industry and occupation sectors for potential self-employment and entrepreneur training. *Arts, Design, Entertainment, Sports, and Media (SOC: 27)* and *Personal Care & Service (SOC: 39)* Occupation have higher odds of being *self-employed* (versus in *wage-and-salary* employment) than *Management (SOC:11)* occupations. To some extent, those sectors provide a special niche differing from most workforce training programs focusing on skills upgrading. In contrast, workers in most sectors that experienced employment growth in Maryland from 2017-2022 are among the lowest odds of being *self-employed* (versus in *wage-and-salary* employment).

By identifying propensities for six different types of self-employment, it helps workforce service programs to customize certain related training to specific types of *self-employment* workers' desire. Among Maryland self-employers, male self-employed workers are more likely to be *new* (versus *incumbent*), *incorporated* (versus *unincorporated*), and *full-time* (versus *part-time*) self-employers; younger, African (versus White) American, less educated self-employed workers are more likely to be *new* or *full-time* (versus respectively *incumbent* or *part-time*) self-employers; being employed in the prior month is more likely to be associated with *incumbent* (versus *new*) self-employment in the current month. Among Maryland self-employers and compared to *Management (SOC: 11)* occupations, the odds of being *new* (versus *incumbent*) self-employers in *Healthcare Support (SOC: 31)* occupations are 7.55 times as high, *Office & Administrative Support* occupations *(SOC: 43)* are more likely to be *new* (versus incumbent) self-employers and *part-time* (versus *full-time)* self-employers, *Construction & Extraction occupations (SOC: 47)* and *Transportation and Material Moving occupations (SOC: 53)* are more likely to be *new* (versus *incumbent*) self-employers, *Installation, Maintenance, and Repair occupations (SOC: 49)* are more likely to be *full-time* (versus *part-time*) self-employers and *unincorporated* (versus *incorporated*) self-employers. As *incorporated* and *new* self-employment often create jobs, the high odds of *incorporated* (versus *unincorporated*) self-employment in *Management (SOC: 11)* occupations and the high odds of new (versus *incumbent*) self-employment in *Healthcare Support (SOC: 31)* occupations helps two sectors to be in the short list of sectors with employment growth from 2017 to 2022.

This study also helps identify weakest links in self-employment training. The models in the study show that among Maryland workers, male, older, or better educated workers are more likely to be *self-employed* instead of in *wage-and-salary* employment. This means female, poorly educated, younger workers who cannot find an eligible wage-and-salary employment are particularly the ones needing help if to be trained for self-employment.

Compared to the national average, Maryland workers have a clearly higher WFH rate, particularly in *Management* occupations *(SOC: 11)* and industry sectors of *Real Estate (NAICS:53), Other Services (NAICS:81), and Public Administration (NAICS:92).* With WFH becomes an integral part of work norm, those sectors will continue prosper, while the others probably need to accommodate this new WFH or hybrid norm to attract the best talents.

The study identifies who are more likely to work from home; this would help workforce services to accommodate the changing labor supply. Among Maryland workers, female and better educated workers with higher family income are more likely to work from home. Compared to *Management (SOC: 11)* occupations, *Business & Financial Operations (SOC: 13)* and *Computer & Mathematical Occupations (SOC: 15)* are more likely to work from home. Compared to *Agriculture (NAICS: 11)*, M*anufacturing (NAICS: 31-33)*, *Information (NAICS: 51)*, *Finance & Insurance (NAICS: 52), Real Estate (NAICS: 53)*, *Professional Services (NAICS: 54)*, *Education (NAICS: 61)*, *Healthcare (NAICS: 62)*, *Other Services (NAICS: 81)*, and *Public Administration (NAICS: 92)* have higher WFH odds. Compared to observations with unspecified county locations, *Harford County* has lower WFH odds, while *Montgomery, Prince George's,* and *Baltimore City* have higher WFH odds. While not all jobs are can be done via telework, female workers or workers in locations like Harford County would probably benefit from WFH incentives or assistance.

With sectoral disparities, it is not surprising that in Maryland, WFH jobs are paid averagely $144 more each week than non-WFH jobs. With telecommunicating technology grows, non-WFH jobs might have to adapt to attract the best talents or to be more efficient. Otherwise, the digital divide could become more real in years to come.

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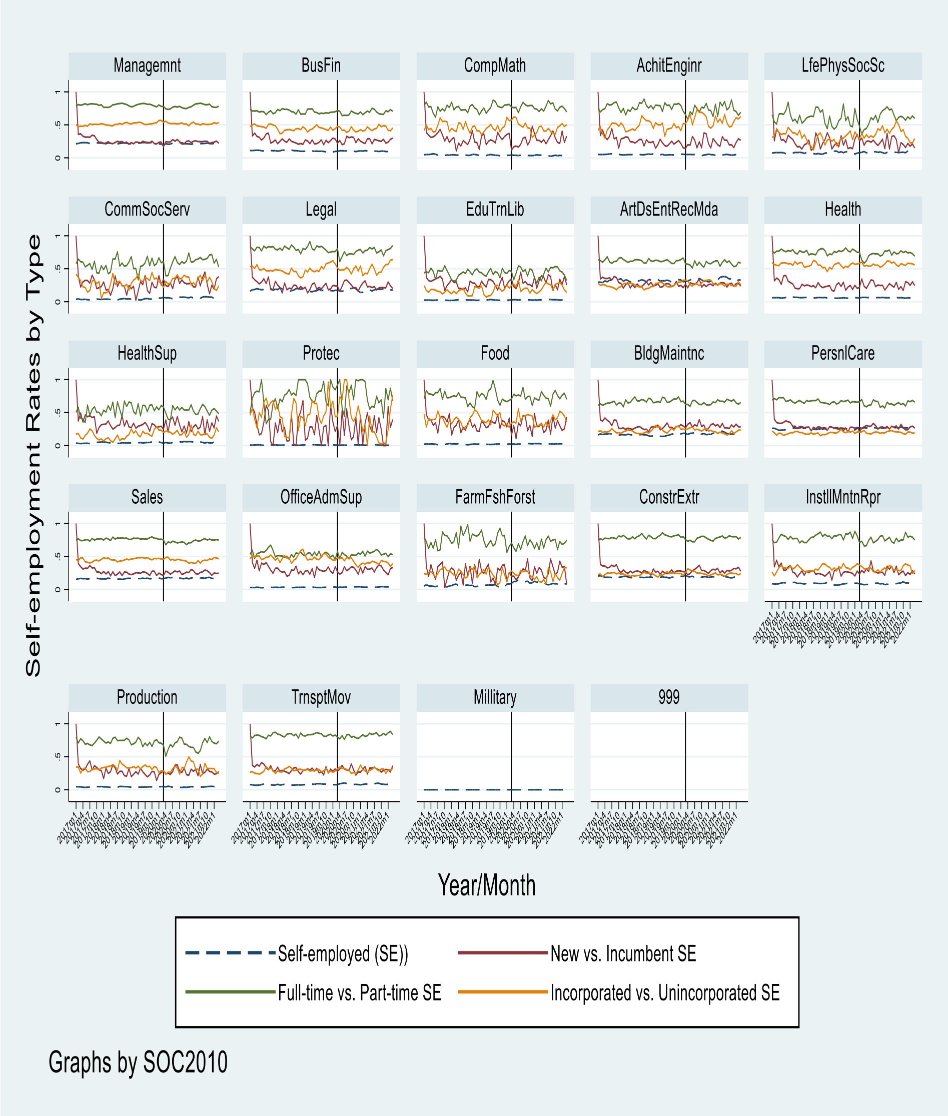
Appendix

Figure A. Self-Employment Trends by Occupation Sectors, USA vs. Maryland

USA



Maryland

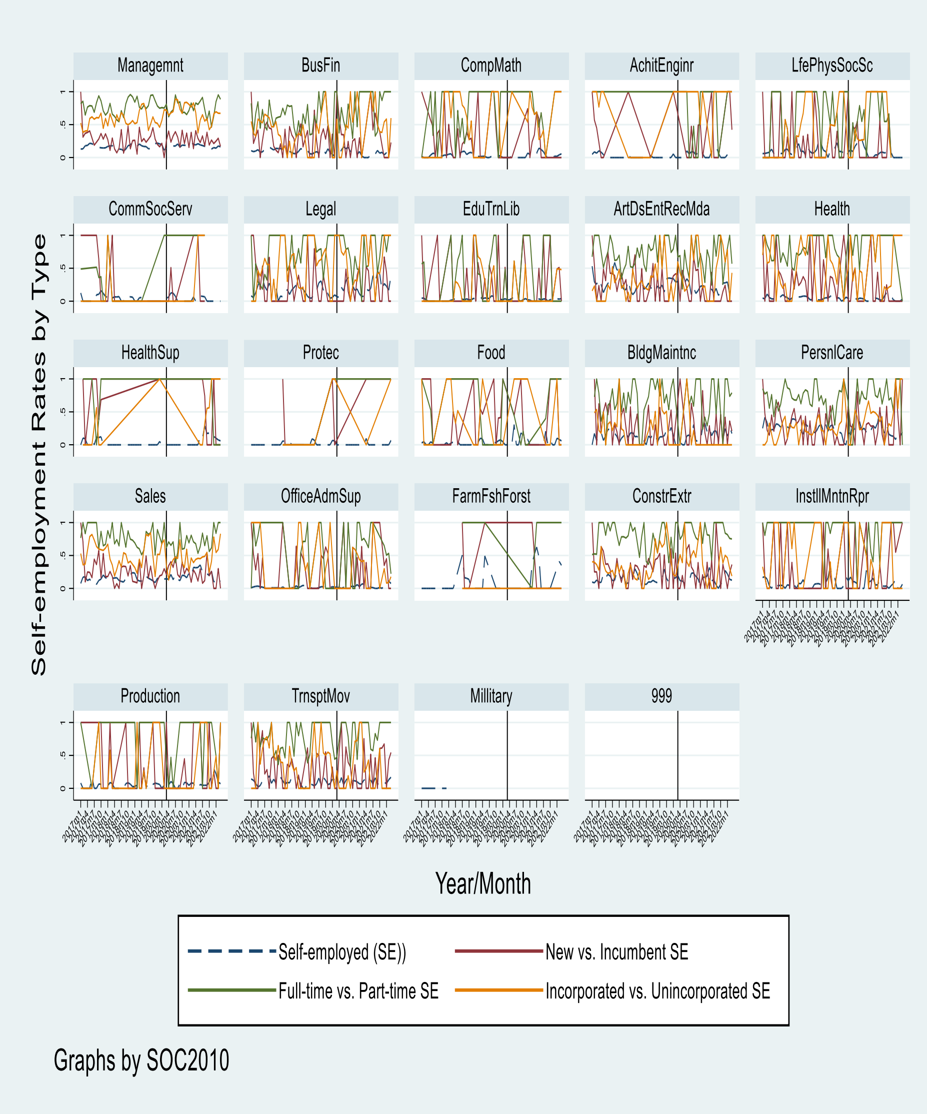


Figure B. Self-Employment Trends by Industry Sectors, USA vs. Maryland

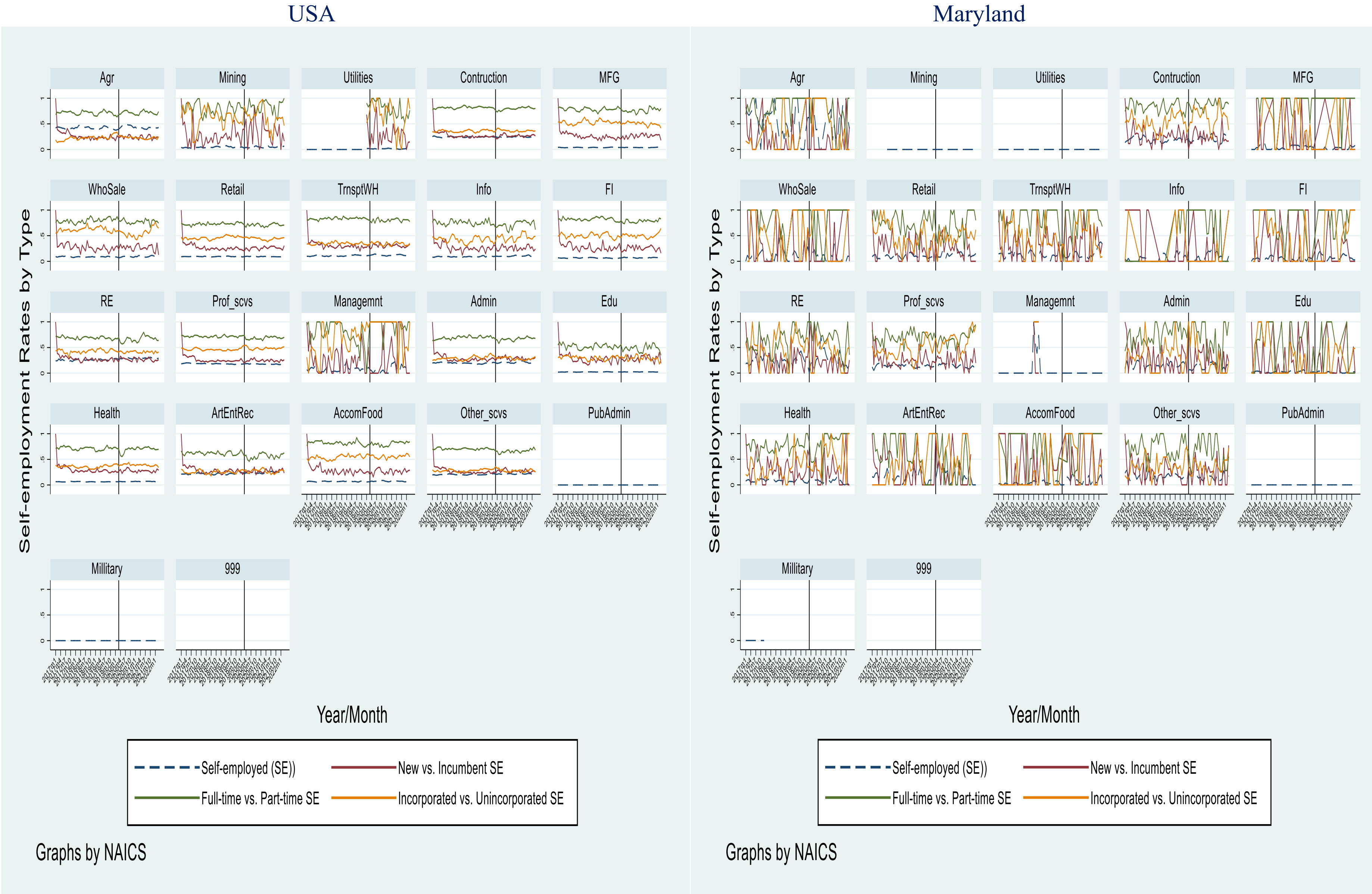


Table A. Correlation Matrix for Self-Employment

	SE_WS	Male	AgeGr25	Race	Educ	Marrie~p	Childi~H	Fam Inc	Employ~p
SE_WS	1.0000								
Male	0.0599	1.0000							
AgeGr25	0.1301	0.0158	1.0000						
Race	-0.0228	-0.0308	-0.0507	1.0000					
Educ	-0.0014	-0.0820	0.0088	-0.0101	1.0000				
Married Sp	0.0674	0.0773	0.1406	-0.0752	0.1494	1.0000			
Child in HH	-0.0043	-0.0457	-0.0854	0.0473	0.0204	0.3580	1.0000		
Fam Inc	-0.0096	0.0243	0.0468	-0.0747	0.3726	0.3071	0.0982	1.0000	
Employed_LM	0.0231	-0.0030	0.0214	-0.0244	0.0633	0.0587	0.0127	0.1315	1.0000
Num Jobs 5w a	0.0390	-0.0178	0.0063	-0.0126	0.0818	0.0237	0.0110	0.0837	0.5479
SOC2010	-0.0180	0.0468	-0.0279	0.0313	-0.4855	-0.1219	-0.0035	-0.3268	-0.0684
NAICS	-0.1416	-0.1815	0.0290	0.0628	0.2112	-0.0005	0.0085	0.1145	0.0391
county	0.0119	0.0055	0.0087	-0.1071	-0.0301	0.0488	0.0154	-0.0338	0.0081
COVID	-0.0004	0.0037	0.0247	0.0385	0.0600	-0.0049	-0.0125	0.0595	-0.0362
Year Month	-0.0018	-0.0013	0.0365	0.0322	0.0533	-0.0099	-0.0213	0.0651	-0.0254

	Num Job~a	SOC2010	NAICS	county	COVID	Year Month
Num Jobs 5w a	1.0000					
SOC2010	-0.0543	1.0000				
NAICS	0.0389	-0.2335	1.0000			
county	0.0146	-0.0111	-0.0361	1.0000		
COVID	-0.0233	-0.0147	-0.0133	0.0171	1.0000	
Year Month	-0.0175	-0.0208	-0.0128	0.0115	0.8447	1.0000

Table B. Correlation Matrix for WFH and Earnings

	Weekly Earn	WFH	Male	AgeGr25	Race	Educ	Marrie~p	Childi~H	Fam Inc
Weekly Earn	1.0000								

WFH	0.3205	1.0000							
Male	0.1558	-0.0544	1.0000						
AgeGr25	0.0945	-0.0079	0.0044	1.0000					
Race	-0.0544	0.0278	-0.0389	-0.0070	1.0000				
Educ	0.4432	0.4098	-0.1104	-0.0202	0.0257	1.0000			
Married Sp	0.2248	0.0738	0.0741	0.1583	-0.0959	0.1488	1.0000		
Child in HH	0.1144	0.0220	-0.0214	-0.0398	0.0121	0.0470	0.3782	1.0000	
Fam Inc	0.4285	0.2395	0.0062	0.0345	-0.0857	0.3586	0.3176	0.1408	1.0000
Employed LM	0.1032	0.0645	-0.0236	0.0371	-0.0101	0.0516	0.0355	0.0218	0.0487
Num Jobs 5w a	0.0150	0.0506	-0.0199	-0.0005	0.0012	0.0472	-0.0371	0.0278	0.0292
SOC2010	-0.4254	-0.3669	0.0909	0.0092	0.0284	-0.5031	-0.1293	-0.0098	-0.3562
NAICS	0.1289	0.2178	-0.1750	0.0689	0.0483	0.2413	0.0224	-0.0002	0.1343
county	0.0302	-0.0050	0.0118	-0.0273	-0.0636	0.0293	0.0487	0.0441	-0.0292
Year Month	0.0251	-0.2115	0.0131	0.0052	0.0016	-0.0216	0.0073	-0.0317	-0.0060

	Employ~W	Num Job~a	SOC2010	NAICS	county	Year Month
Employed LW L1.	1.0000					
Num Jobs 5w a L1.	0.4153	1.0000				
SOC2010	-0.0620	-0.0388	1.0000			
NAICS	0.0104	0.0521	-0.2661	1.0000		
county	-0.0054	0.0049	-0.0334	-0.0312	1.0000	
Year Month	0.0510	0.0225	-0.0072	0.0117	-0.0201	1.0000